Handbook of Pricing Research in Marketing

Edited by Vithala R. Rao

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Edited by

Vithala R. Rao

Cornell University, USA

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He currently serves as associate editor for *Quantitative Economics and Marketing*. He is also an area editor for *Marketing Science* and *Management Science*. He won the 2001 John D.C. Little Best Paper Award and 2001 Frank Bass Best Dissertation Award, along with his co-authors, for his contribution to the understanding of targeted pricing with imperfect targetability.

Foreword

Editing a handbook is an opportunity to organize a field. My marketing colleague, Vithala Rao, seems to have been preparing for this for 24 years, judging from his paper, 'Review of Pricing Research in Marketing: The State of the Art', written in 1984.

At its finest grain, Vithala's organization of pricing research starts with 26 chapters written by top researchers in areas of their personal expertise. Coverage is remarkably comprehensive. The *Handbook* divides roughly into thirds: Part I – Introduction/Foundations, Part II – Pricing Decisions and Marketing Mix, and Part III – Special Topics, the latter emphasizing recent developments. I am also completely impressed with Vithala's people organizational skills in making 26 chapters with 26 sets of authors and reviewers actually happen.

The *Handbook* takes an active view of pricing, which I applaud. The 'Introduction' contrasts pricing research in marketing with that in microeconomics, pointing out that marketers are oriented toward achieving the objectives of the firm. I relate to this, since I come from the OR/MS tradition, which focuses on decision-making and decision support.

The ubiquity of price as a control variable has pursued me all of my marketing life. In 1969, as a neophyte consultant, I co-built a marketing-mix model at Nabisco for Oreos, 'America's Favorite Cookie'. Our goal was to support marketing management in its annual plan. We had monthly historical data with which to calibrate the model. It was then I first learned that what many academics were interpreting as a price variable was really promotion. Price had not gone away; the marketing mix needs both. I was being introduced to pricing research.

To give the reader a taste of Vithala's *Handbook*, I sample three chapters:

Chapter 20: 'Pricing under network effects' (Liu and Chintagunta)

The hallmark of networks is that they become more valuable to everybody as more people join them. Although network effects are as ancient as a middle-east bazaar, the Internet has newly thrust them in our faces with innovations such as multi-person online games.

Liu and Chintagunta describe pricing issues under network effects as reported in the theoretical literature, including static pricing, dynamic pricing, and nonlinear pricing. The authors, however, lament the state of empirical research in the field. To quote them, 'we are still not well equipped to provide normative guidance on firm's pricing strategies in real industry settings'. Thus one researcher's problem will be a future researcher's challenge.

Chapter 18: 'Strategic pricing: an analysis of social influences' (Amaldoss and Jain)

The authors build models of social phenomena that may variously be called conspicuous consumption, prestige, or snobbishness. The models focus on two basic social needs: a desire for uniqueness on one hand and the countervailing need to conform on the other. People buy conspicuous goods not just to satisfy material needs but also because of social desires. Firms that produce such goods tend to advertise the exclusivity of their products and must find an appropriate pricing strategy for them.

A summer 2008 example was AT&T Wireless, which became an exclusive channel for the Apple's new iPhone 3G. Big introductory promotions (with high prices for the iPhone) produced queues of hundreds of people at Apple stores in shopping malls on July 11. I myself was a purchaser (but through AT&T because I was unwilling to wait in queue). My self-analysis is that I was briefly unique and then sank into conformity.

Chapter 19: 'Online and name-your-own-price auctions: a literature review' (Park and Wang)

The authors review pricing mechanisms that have long been known for selling art objects but have suddenly blossomed into multi-billion dollar Internet businesses. The literature review is a service to all of us interested in this economically significant area, either for research or profit. The chapter covers recent theoretical, empirical, and experimental research on the effect of auction design parameters on outcomes, as well as bidding strategies themselves. The field is rich in results, in part because the theoretical work is well balanced by access to field and experimental data.

Perhaps it is the skill of the authors, but I am heartened to see so many concepts and phenomena from the foundations of pricing (as covered in earlier chapters), from marketing generally, and from consumer behavior in particular, show up in this excellent review.

Challenges ahead

A sub-theme throughout the *Handbook* is future research opportunities. In looking around today, I see many examples of practical pricing problems that seem to beg for investigation. Consider the exploding field of advertising on search engines. In the early days of the Internet, when people were proclaiming a 'new economy', many start-ups planned to pay their bills by selling advertising. This dream disappeared in the collapse of the Internet bubble. Then Google found a way to make advertising generate significant revenue. Its pricing mechanism was auctions. Google's revenue growth brought it a high stock price and a huge market valuation. Now Google competitors are trying to make advertising work too. This sounds like a pricing research challenge. The fundamentals presented in Vithala's *Handbook* will be important building blocks. The world is waiting for the right research team.

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I want to thank all the contributors to this *Handbook* for agreeing to contribute and for their care in revising the chapters. I also want to thank all the reviewers, who provided thoughtful comments for revision and thus helped improve the quality of the chapters included here. I sincerely appreciate their support in this venture. Special thanks go to Wilfred Amaldoss, whose encouragement was highly instrumental in my undertaking this project. I am grateful to Professor John D.C. Little for sparing time to compose the foreword to this *Handbook*. I also want to thank my faculty support aides at the Johnson School, Judy Wiiki and Sara Ashman for their administrative guidance in various tasks with lots of cheer. I thank Alan Sturmer of Edward Elgar, who provided invaluable support and guidance in bringing this effort to conclusion, and Caroline Cornish of Edward Elgar for efficiently managing the production of this volume.

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For my wife, Saroj,
and our grandchildren,
Rheya, Vikram, Divya, and Alisha

Introduction

Vithala R. Rao

Introduction

There can be little doubt that pricing decisions are predominant among all the marketing mix decisions for a product (service or business). Pricing decisions interact with other marketing mix decisions and also with the decisions of distribution intermediaries of the firm.

Pricing research occurs in at least two disciplines of microeconomics and marketing. While the pricing research in microeconomics[1] is largely theoretical, research in marketing is primarily oriented toward managerial decisions. Further, pricing research in marketing is interdisciplinary, utilizing economic as well as behavioral (psychological) concepts. Research in marketing emphasizes measurement and estimation issues as well. The environment in which pricing decisions and transactions are implemented has also changed dramatically, mainly due to the advent of the Internet and the practices of advance selling and yield management. Over the years, marketing scholars have incorporated developments in game theory and microeconomics, behavioral decision theory, psychological and social dimensions, and newer market mechanisms of auctions in their contributions to pricing research. Examples include applications of prospect theory, newer conjoint analysis methods for measurement of price effects, newer market mechanisms of auctions, use of game theory in dealing with pricing along the distribution channel, and models that describe practices of advanced selling and yield management.

This *Handbook* consists of 26 chapters and is an attempt to bring together state-of-the-art research by established marketing scholars on various topics in pricing. The chapters are specifically written for this *Handbook*. The chapters cover various developments and concepts as applied to tackling pricing problems. Based on a thorough academic review, the authors have revised their initial drafts of chapters.

Overview of chapters in the *Handbook*

The chapters are organized into three major parts, labeled Parts I (8 chapters), II (9 chapters) and III (9 chapters). Part I covers topics that are in some sense fundamental to pricing research. Part II covers topics that deal with selected pricing decisions and marketing mix, while Part III covers some special topics that are emerging in pricing research.

[1] The two volumes of published articles on pricing tactics, strategies and outcomes edited by Waldman and Johnson (2007) epitomize the significant amount of research in microeconomics. A variety of topics is covered in the articles included in these volumes; examples are: pricing product line, pricing and consumer learning, collusive behavior, empirical studies of pricing strategies leasing and couponing.

Part I (eight chapters): fundamental topics

The chapter by Rao and Kartono describes the results and analyses of reported use of some 19 possible pricing strategies based on a survey among pricing decision-makers conducted in three countries. Three most frequently used strategies are the cost-plus, price signaling, and perceived value pricing, with considerable differences among the three countries. Their chapter also shows the relationships between the reported usage of strategies, and several determinants and pricing objectives. These descriptive results may form the basis for developing richer mathematical (possibly game-theoretic) models for optimal choice of pricing strategies.

Chapter 2, by Jedidi and Jagpal, focuses on the methods for measuring willingness to pay (WTP) or reservation price for a product or service, and using those measures in various pricing decisions such as bundling, quantity discounts and product line pricing. This concept is fundamental to both the theory and practice of pricing. In addition to self-stated WTP, the authors discuss methods for estimating WTP from actual purchase data, contingent evaluation data, conjoint methods and experimental auctions. They call for additional research on comparing the methods as well as developing newer methods. One example of a newer method is to measure reservation price as a range (Wang et al., 2007).

Chapter 3 by Liu, Otter and Allenby describes approaches to measure own- and cross-price effects particularly when there is a large number of offerings in a product category. This problem arises particularly in the retail context. They describe methods to reduce the dimensionality of the problem by employing economic theory of choice and demand, and Bayesian methods to augment the information contained in the data. Extension to estimating dynamic price effects is a challenging research issue, as identified by the authors.

Chapter 4 by Krishna focuses on the effects of price that cannot be accounted for by the intrinsic price itself. These effects, called 'behavioral effects', arise due to the way individual consumers are influenced by price presentation in comparison to an externally provided reference price or presentation of a promotional offer as absolute reduction in dollars or as a percentage reduction relative to normal price. The author discusses a variety of these effects using both laboratory experimental data and data of actual purchases. Clearly more work is possible in this fascinating area.

Chapter 5 by Ratchford deals with consumer search behavior and prices. The author reviews empirical studies that support the basic conjecture of Stigler made some 40 years earlier, namely that consumer search is costly and that it will create price dispersion. The review summarizes theoretical models of optimal search, and describes how costly search may affect the behavior of markets. Two of the key results in this literature are that price dispersion should exist in equilibrium, and that differences in search costs provide a motive for price discrimination. Also, there is heterogeneity of search behavior among consumers. The author also reviews the impact of the Internet on price dispersion. As he points out, there is need to develop models of pricing and price dispersion that are more closely related to actual seller behavior.

Chapter 6 by Chan, Kadiyali and Xiao emphasizes the need to specify appropriate assumptions for the behavior of consumers and firms to understand market outcomes. The resulting structural models suitably estimated will be useful for conducting simulations in determining optimal price policies for a varying set of market conditions. While this line of research is distinct from the reduced-form approach often employed in

marketing research, it will undoubtedly enrich our understanding of the drivers of market prices. The structural approach offers possibilities to incorporate alternative behavioral assumptions and alternative ways of interactions among agents. It constitutes a step in the right direction for incorporating the impact of competition into pricing research.

Chapter 7 by Thomas and Morwitz describes implications of the anchoring, representativeness and availability heuristics on the judgments consumers make on the magnitude of prices of products or services and the order of numerical digits in the prices. For example, consumers may judge the differences to be large for pairs with easier computations than for pairs with difficult comparisons. These authors comment that pricing managers should decide not only the magnitude of the optimal price but should also pay attention to how the digits are arranged. This general area offers opportunities for exciting experimental research.

In Chapter 8, Anderson and Simester discuss the literature on the effectiveness of price cues that documents examples of firms exploiting their use. A price cue is any marketing tactic used to persuade customers that prices (posted) offer a good value. The authors review extant literature, document the effectiveness of price cues and present evidence for the economic explanation that customers respond to price cues if they lack sufficient knowledge of prices and if they cannot evaluate whether prices offer good value.

Part II (nine chapters): pricing decisions and marketing mix

Chapter 9 by Chatterjee provides a comprehensive review of the normative models developed in the literature on strategic pricing for new products and services that incorporate various factors such as consumer learning, diffusion, cost reduction and competition. This chapter also contains a review of relevant empirical research on the use of penetration pricing or skimming pricing strategies. There are interesting opportunities for building normative models to deal with nontraditional pricing schemes, such as pricing to maximize customer lifetime value and auctions on the Internet.

Chapter 10 by Chen reviews developments in pricing a product line, defined as the set of products or services sold by a firm that provide similar functionalities and serve similar needs and wants of consumers. The products in the line can be vertically or horizontally differentiated, or both. Factors such as customer self-selection and competition are included in the models and results reviewed are intuitively appealing. Various directions for future research are also suggested.

Chapter 11 by Venkatesh and Mahajan provides a comprehensive review of the design and pricing of product bundles, a practice that is growing in the wake of high technology and e-Commerce. The authors have drawn a set of guidelines for bundle pricing based on a large body of traditional models in the literature as well as newer methodologies. Opportunities exist in this area for both behavioral research and analytical modeling.

Chapter 12 by Pauwels and Srinivasan describes the issues involved in pricing of national brands relative to store brands (or private label brands) in light of the increasing quality equivalence between them. The authors suggest that in most cases national brands possess some degree of pricing and market power over store brands. They discuss the sources of such power in terms of price premium, volume premium and margin premium, and suggest directions for future work.

Chapter 13 by Narasimhan describes the tradeoffs involved in using trade promotions versus lowering price or advertising in the B2C markets. The chapter reviews different

types of trade promotions, the rationale behind using them, the potential impact on the channel partners, and managerial implications. The chapter concludes with several suggestions for future research such as the need to examine the role of trade promotions in a firm's overall pricing strategy.

Chapter 14 by Zhang discusses how prices can be customized for specific targets. This problem has become quite significant due to the unprecedented capability of firms to store and process past buying information on customers and the ability of firms to tailor prices to individual customers. The chapter answers such questions as 'Is target pricing beneficial to firms?', 'What is the best way of designing incentives if targeted pricing is followed?', and 'Is target pricing beneficial to society as a whole?' Some surprising results are discussed, as well as future directions for research in this emerging area.

Chapter 15 by Sudhir and Datta provides a critical review of research in pricing within a distribution channel. Specifically, the authors review the literature on three decisions, which vary in terms of planning horizon, on retail pass-through, pricing contracts and channel design. They also review the empirical literature on structural econometric models of channels and suggest directions for future research. For example, opportunities exist to study channel behavior in the presence of nonlinear pricing contracts (the topic of Chapter 16) and developing methodologies that endogenize retailers' decision to carry the product.

Chapter 16 by Iyengar and Gupta covers nonlinear pricing and related multi-part pricing paradigms, and reviews the extant literature. The authors point out that while two-part tariffs may be nearly optimal in many settings, there is a need to examine more complex pricing schemes. They also discuss the challenges involved in analyzing pricing schemes due to the two-way relationship between price and consumption (as in telephone pricing) and show some approaches to tackling such problems. They present some empirical generalizations and identify areas for future research.

Chapter 17 by Seetharaman focuses on how state dependence and reference prices affect consumer choices over time and their pricing implications for firms competing in oligopolistic markets. Based on a review of various econometric models of dynamic pricing, he identifies research opportunities for incorporating reference price effects in descriptive models of what firms actually do in practice.

Part III (nine chapters): special topics

Chapter 18 by Amaldoss and Jain focuses on how social needs such as prestige influence purchase decisions. The authors show that snobs can have an upward-sloping demand curve only in the presence of consumers who are conformists. They also investigate how social needs may influence the prices and qualities of the products that consumers choose to buy. There are opportunities to extend their one-period game to deal with multi-period decisions and also to incorporate reference group effects and brand equity.

Chapter 19 by Park and Wang provides a review of recent research on the emerging market mechanism of online auctions. Their survey covers theoretical, empirical and experimental research on the effects of auction design parameters of minimum price, buy price, and duration, bidding strategies and competition. They also discuss the name-your-own-price mechanism. They call for additional empirical research on the effects of auction design parameters, experiments to study the effects of bidder behavior, and studies on bidder learning. Research in this area will undoubtedly proliferate in the future.

Chapter 20 by Liu and Chintagunta deals with the subject matter of pricing under network effects. They review the early literature on static pricing under network effects that focused on the effects of price expectations and the multiple equilibria problem. They state that penetration pricing has been found optimal under various scenarios. Their review of analytical literature of pricing under network effects connects with other literatures. Noting that empirical research is scarce in this area, they identify issues that limit such research.

Chapter 21 by Xie and Shugan covers how prices should be set under the new paradigm of advance selling that has been facilitated by developments in technology. They discuss how the profit advantage of advance selling is quite general and is not severely restricted by industry structures. They also show that simply offering advance selling can improve profits because it separates purchase and consumption, which creates buyer uncertainty about their future product/service evaluation and removes seller information disadvantage. They identify several research opportunities in such areas as the evaluation of consequences and profitability of advance selling in many new situations, and sellers offering multiple advance periods.

Chapter 22 by Kimes discusses the strategic role of price in revenue management. Revenue management has been practiced in the airline, hotel and car rental industries for some time and is receiving attention in other industries such as broadcasting and golf. The chapter reviews the literature on models of revenue management allocation and pricing, and the practices in industry. There are opportunities to incorporate competitive reactions in such models.

Chapter 23 by Kina and Wosinska discusses the various institutional characteristics that affect pricing of prescription drugs. The chapter provides insights on the role of various players in this complex price-setting problem. The authors identify three distinct areas for future research – clarifying the market, ways to optimize the current system, and the influence of changes in the regulatory and institutional environment on pricing pharmaceutical products. Research opportunities in this topic are considerable.

Chapter 24 by Liu and Weinberg describes how pricing decisions particularly challenge not-for-profit organizations, which have a social rather than a profit objective function. The authors show how the pricing models in the nonprofit sector are different from those of for-profit businesses. The chapter surveys findings in the theoretical and empirical research on nonprofit organizations. The authors identify special issues in relating constructs of consumer taste and willingness to pay commonly employed in pricing models for the nonprofit sector. They describe interesting research opportunities in examining the effects of price–quality and product differentiation in the nonprofit sector.

Chapter 25 by Shoemaker and Mattila focuses on the pricing issues in the services sector in general. The authors review how the special characteristics of services such as intangibility and simultaneous production and consumption offer unique challenges to the firm in setting prices. Their framework is an attempt to show how various factors affect consumers' reservation price for a service and how this interacts with the way a firm can formulate service offers to gain maximum revenues. They provide illustrations of practice and suggest research possibilities in this important sector of the economy.

The final chapter, Chapter 26 by Ho and Su, provides a selective review of pricing models that are of interest to operations management researchers. The authors review developments in four specific pricing models, two of which are based on inventory (EOQ

and Newsvendor), dynamic pricing models, and queuing models. They show how firms' pricing decisions serve as an important lever to shape consumer behavior and optimize profits. One common theme of this chapter is that consumers respond strategically and actively engage in operational decision-making. The authors suggest opportunities to extend this line of work to conditions that relax the rationality assumptions.

Research directions

Interestingly, several of the research directions identified in my previous reviews of pricing literature (Rao, 1984 and 1993) have been pursued. In a similar manner, I hope that the research topics mentioned in the chapters of this *Handbook* will inspire future researchers. It is possible that future research on pricing will be tilted toward the newer pricing mechanisms that are aided by technology.

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PART I

INTRODUCTION/ FOUNDATIONS

1 Pricing objectives and strategies: a cross-country survey

*Vithala R. Rao and Benjamin Kartono**

Abstract
This chapter reports the results of a descriptive study on pricing objectives and strategies based on a survey among managers in three countries (USA, India and Singapore). The survey instrument was developed using a conceptual framework developed after an analysis of the extant literature on pricing objectives, strategies and factors that influence the choice of pricing strategies. Data were collected on firms' utilization of 19 possible pricing strategies, pricing objectives and various pricing determinants. The responses were used to estimate logit models of choice of pricing strategies. The results reveal interesting differences among the three countries as well as the use of different strategies. The implications of this descriptive study for guidance of pricing are discussed.

1. Introduction

Pricing is the only element of the marketing mix that brings revenues to a firm. While there are extensive theories/models of how a firm should price its goods and services, descriptive research on how firms make their pricing decisions is sparse in the literature. One may argue that descriptive research can help model builders in developing more realistic models for pricing. Various researchers in the past have been concerned about the practice of pricing and the degree to which it departs from theory. Yet our understanding of the pricing processes is still in its infancy.

The present chapter attempts to contribute to the descriptive pricing literature by not only examining the problem across various industries and countries, but also accounting for the effect of another important element of the pricing decision: the company/product conditions, market conditions, and competitive conditions that influence the pricing strategy adopted by the firm (collectively labeled as 'pricing strategy determinants' by Noble and Gruca, 1999). To complete the analysis, we also consider another element that can play a part in influencing pricing decisions, namely demographic characteristics of the firms in question as well as those of the individuals within the firms. In the sections that follow, we review extant descriptive research on pricing, present a conceptual framework that illustrates how firms determine their choice of pricing strategy, and describe the results of an empirical study that we conducted in three countries to assess the applicability of the framework.

* We thank Subrata Sen for providing valuable comments on an earlier draft of this chapter, and Shyam Shankar for his assistance in analysis of the survey data.

2. Selected review of past research

Descriptive research on how firms decide on the specific strategies[1] of pricing is quite limited in the literature. Table 1.1 summarizes the main findings of seven studies beginning with the one by Hall and Hitch (1939) and ending with Avlonitis and Indounas (2005). All of these studies utilized either mail questionnaires and/or personal interviews to obtain data from samples of managers with a view to determining their pricing and profit objectives while pricing their products and services.

Table 1.1 A summary of past studies on pricing objectives and strategies of firms

Author(s)	Date	Objectives of the study	Methodology employed	Some findings
Hall and Hitch	1939	To determine the way business executives decide what price to charge for their products	Use of a questionnaire and lengthy interviews among 38 business executives	Ten of the firms used conventional or full cost policy in setting prices, and methods for computing full cost varied among the firms. A large fraction of firms do not adopt the principle of marginal revenue equals marginal cost in setting prices. Firms take competitor reaction into account while pricing their products.
Lanzillotti	1958	To determine the pricing objectives of a sample of large US industrial firms	Postprandial research – lengthy interviews conducted at two points in time among officials of firms	Several pricing objectives such as achieving a target rate of return, stabilization of price and margin, realizing a target market share, and meeting or preventing competition were uncovered in this study.
Shipley	1981	To determine pricing and profit objectives of British manufacturing firms	Use of a mail questionnaire sent to a stratified sample of sales and marketing directors listed in KOMPASS; responses obtained from 728 firms	General finding that there is a considerable heterogeneity of pricing and profit objectives that vary with size and number of competitors. Firms pursue a multiplicity of objectives while pricing their products. One-third of the firms do not list profit objective.
Samiee	1987	To examine the role of pricing in marketing plans of US- and	Mail survey among 104 US- and 88 foreign-based companies	While there are differences in the role of pricing among the two groups of firms, pricing decisions are found to be more centrally made

[1] In the literature, the term 'pricing method' is sometimes used in place of the term 'pricing strategy'. For example, Oxenfeldt (1973), Diamantopoulos and Mathews (1995) and Avlonitis and Indounas (2005) use the former while articles such as Tellis (1986) and Noble and Gruca (1999) adopt the latter. In this chapter, we use both terms interchangeably.

Table 1.1 (continued)

Author(s)	Date	Objectives of the study	Methodology employed	Some findings
		foreign-based companies operating in the USA as well as how pricing decisions are made and the objectives for pricing	and personal interviews among executives from 12 such companies	in the US-based companies. Pricing objectives are found to be similar; the major objectives are: satisfactory ROI, maintenance of market share, reaching a specified profit goal, seeking largest market share, and profit maximization.
Jobber and Hooley	1987	To examine pricing objectives for both manufacturing and service companies, differences by stage of market evolution, size of the firm, and the relationship between pricing objectives and performance	Mail survey among 1775 members of the UK Institute of Marketing; questionnaire developed using interviews among 150 executives	Pricing objectives are found to vary by stage of market evolution and size of the firm. For example, maximization of current sales revenues is found to be more important for emerging/new markets as compared to growth markets. Profit maximization and market share attainment/maximization were similar by stage of the market evolution. Small and medium-sized firms used profit maximization as pricing objective more than large firms. Both positive and negative relationships between pricing objectives and performance were found.
Noble and Gruca	1999	To organize the existing theories of pricing and to determine which factors account for the use of specific strategies	Based on extensive literature search, a questionnaire was constructed and administered to 270 managers in industrial firms in the USA. The researchers developed logistic regression models that relate the strategy choices to a variety of factors deemed relevant to pricing strategy.	In general, the authors found that managers' pricing strategy choices are consistent with normative pricing research. This conclusion applies to four specific stets of pricing strategies: new product pricing, competitive pricing, product line pricing and cost-based pricing.

Table 1.1 (continued)

Author(s)	Date	Objectives of the study	Methodology employed	Some findings
Avlonitis and Indounas	2005	To explore the association between pricing objectives and strategies in the services sector	Personal interviews involving 170 companies from six different service sectors in Greece. Logistic regression was used to assess the impact of pricing objectives on the adopted strategies.	The key pricing objectives adopted are fundamentally qualitative in nature and determined with customers' needs and satisfaction in mind, but the pricing strategies used tend to be firm-centric, with the cost-plus method and pricing according to average market prices adopted by most of the firms.

To illustrate, the study by Lanzillotti (1958) utilized personal interviews among officials of a purposive sample of 20 large US corporations and attempted to understand various goals pursued by their pricing policies. He found that these firms had a varied set of goals such as increasing market share, maintenance of market share, achieving a 'fair' return on investment, achieving a minimum rate of return, stabilization of prices, and matching competitor prices. Noble and Gruca (1999) adopted the same basic approach and developed a comprehensive list of factors that affect the choice of pricing strategies of firms. Further, they developed statistical relationships (*à la* the logit model) between the choice of a pricing strategy and a number of determinants of that choice. They identified the factors using normative pricing research and other conjectures about the determinants. More recently, Avlonitis and Indounas (2005) explored the relationship between firms' pricing objectives and their corresponding pricing strategies in the services sector using a sample of 170 Greek companies and found clear associations between specific strategies and objectives.

Several researchers have studied the issue of price stickiness, which is broadly related to that of pricing strategies. The question here is how often firms change prices of products and services they offer. A significant example of this research theme is the extensive study by Blinder et al. (1998), who use interviews among executives to understand why prices are sticky in the US economy; their conclusions are that price stickiness is the rule and not an exception, and that business executives do not adjust prices based on macroeconomic considerations. There is some ongoing work by Bewley (2007), who is conducting interviews among business executives to look at the issue of price stickiness; he reaches a somewhat opposite conclusion that price rigidity is far from being the rule and that prices for a large volume of trade are flexible. In contrast to the studies based on interviews, Lien (2007) analyzes micro-data at the firm level reported in quarterly surveys in Switzerland and concludes that inclusion of macroeconomic variables adds only marginally to the explanatory power of a price adjustment probability model that includes firm-specific variables. A similar study is reported by Cornille and Dossche (2006), who use Belgian data on firm-level prices reported for the computation of the Producers' Price Index and find that one out of four Belgian prices changes in a typical month.

While these studies have offered a number of insights into how firms set prices, more empirical research needs to be done to better understand the price-setting process and, in particular, the relationship between firms' pricing objectives, pricing strategies and other elements of the pricing decision. Indeed, Avlonitis and Indounas (2005) state that their extensive review of the literature revealed a lack of any prior work investigating the potential association between a firm's pricing objectives and pricing methods, and that their work is a first attempt at studying this issue empirically within the context of the service industry. The present chapter attempts to further close this gap in the pricing literature by studying how firms' pricing strategies may be affected by their pricing objectives and various firm, market, and competitive conditions. The study was done on firms operating in three countries (USA, India, and Singapore) across a variety of industries and also examines the relationship between the firms' pricing strategies and selected demographic characteristics of the firm.

3. Conceptual framework for pricing decisions

In general, the factors that affect a firm's choice of a pricing strategy can be classified under two broad categories: the pricing objectives of the firm, and pricing strategy determinants. The latter refers to the various company/product conditions, market and customer (consumer) conditions, and competitive conditions that may influence the pricing strategies adopted. In addition, because the data on pricing choices of firms are usually collected by the survey method from managers, certain demographic characteristics of the individual respondents will also matter. Figure 1.1 shows the conceptual framework we adopt in this chapter. It follows the approach of Noble and Gruca (1999), and develops statistical relationships between the choice of a pricing strategy and various relevant factors. Unlike Noble and Gruca (1999), however, in addition to examining the relationship between pricing strategy determinants and the choice of strategy, our framework also looks into the effect of pricing objectives as well as respondent and firm characteristics (such as the respondent's degree of influence in pricing decisions and the size of the firm) on the pricing strategy adopted.

We established our list of possible pricing objectives for the firm based on Diamantopoulos and Mathews (1995, ch. 5). Based on extensive empirical evidence obtained over a two-year period from an in-depth study of a large, oligopolistic manufacturing firm in the medical supplies industry, the authors developed a comprehensive list of possible objectives that managers may seek to accomplish through their pricing decisions. Next, we developed our list of pricing strategy determinants based on the comprehensive outline given in Noble and Gruca (1999). In addition to the determinants studied by the authors, we extended the list to include a number of other determinants relevant to the pricing decision. The complete list of pricing objectives and pricing strategy determinants is given in our empirical study in the next section. Finally, we developed our list of 19 possible pricing strategies which the firm can adopt (for both consumer and industrial markets) through a detailed review of the pricing strategy literature, in particular Tellis (1986) and Noble and Gruca (1999). These strategies[2] cover a variety of possible pricing situations such as competitive

[2] Some of these pricing strategies raise legal issues, but such a discussion is beyond the scope of this chapter; see Nagle and Holden (2006) for discussion.

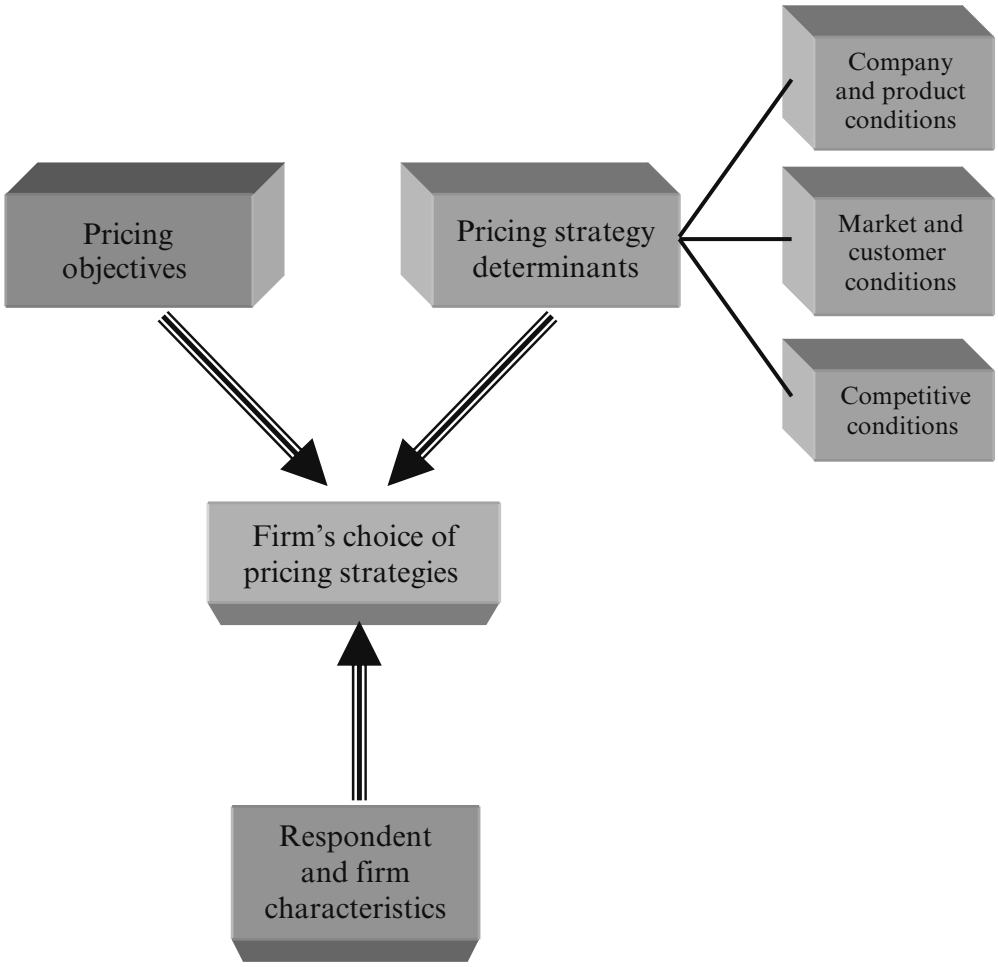

Figure 1.1 The pricing decision: a framework for analyzing a firm's choice of pricing strategies

pricing, cost-based pricing, new product pricing, product line pricing, geographic-based pricing and customer-based pricing. Descriptions of these strategies are given in Table 1.2. One 'new' strategy that we have included, which has not been extensively looked at in the pricing strategy literature, is Internet pricing. We define Internet pricing as the strategy of pricing a product differently on the firm's website compared to the firm's other sales outlets (for example, firms may price their products lower if consumers purchase them online and directly from the firm because of the reduction in costs obtained from not having to pay wholesale and retail margins), and can be thought of as a strategy of pricing differently across channels of distribution (with a focus on direct selling through the Internet). Our reason for including this pricing strategy stems from the increase in Internet commerce that has occurred over the last decade, and we expect this strategy to grow in importance as Internet usage and Internet commerce continue to increase across countries and markets.

Table 1.2 Pricing strategies and their descriptions

Pricing strategy	Description of strategy
1. Price skimming	We set the initial price high and then systematically reduce it over time. Customers expect prices to eventually fall.
2. Penetration pricing	We set the initial price low to accelerate product adoption.
3. Experience curve pricing	We set the price low to build volume and reduce costs through accumulated experience.
4. Leader pricing	We initiate a price change and expect other firms to follow.
5. Parity pricing	We match the price set by the overall market or price leader.
6. Low-price supplier	We always strive to have the lowest price on the market.
7. Complementary product pricing	We price the core product low when complementary items such as accessories, supplies and services can be priced higher.
8. Price bundling	We offer this product as part of a bundle of several products, usually at a total price that is lower than the sum of individual prices.
9. Customer value pricing	We price one version of our product at very competitive levels, offering fewer features than are available on other versions.
10. Cost-plus pricing	We establish the price of the product at a point that gives us a specified percentage profit margin over our costs.
11. Break-even pricing	We establish the price of the product at a point that will allow us to recover the costs of developing the product.
12. Price signaling	We use price to signal the quality of our product to customers.
13. Image pricing	We offer an identical version of the product at a higher price.
14. Premium pricing	We price one version of our product at a premium, offering more features than are available on other versions.
15. Second market discounting	We price this product at very competitive levels for the purpose of exporting or selling in secondary markets.
16. Periodic or random discounts	We periodically or randomly lower the price of this product.
17. Geographic pricing	We price this product differently for different geographic markets.
18. Perceived value pricing	We price this product based on our customers' perceptions of the product's value.
19. Internet pricing	We price this product differently on our Internet website compared to the price we charge through our other sales outlets.

Our review of the extant literature on descriptive, empirical pricing research suggests that ours is the first study that brings together all three key elements of the pricing decision: the pricing objectives, the pricing strategy determinants and, finally, the pricing strategies adopted. In a nutshell, pricing strategies are the means by which the firm's pricing objectives are to be achieved, while the determinants are the internal and external conditions faced by the firm that influence managers' choice of pricing strategies. Our aim is to obtain a more holistic view of the pricing decision, and provide a better understanding of the relationship between each key element of the decision. In addition, the fact that our study was conducted across a number of countries enables us to study any potential differences or similarities in pricing decisions made by firms in different countries. In the next section, we describe our empirical study in detail.

4. Empirical study

The study was conducted via a survey of firms operating in the USA, Singapore and India over a period of about a year beginning in November 2003. The cross-country survey was done primarily by mail and survey questionnaires were sent out to more than 600 firms in each country across a variety of industries. A total of 199 usable responses were obtained, of which 73 were from firms operating in the USA, 54 were from firms operating in Singapore, and 72 were from firms operating in India. The goals of the study were, first, to examine the applicability of our framework in describing the relationship between firms' pricing objectives, pricing strategy determinants and pricing strategies, and, second, to compare the firms' pricing decisions across different countries.

The survey covered products at different stages of the product life cycle (PLC) and spanned a number of different industries and product types. Given the nature of the method used, we cannot claim a representative sample of the population. But the results provide a snapshot of how firms make pricing decisions, as illustrated by the pricing strategies they adopted, their determinants, and the associated pricing objectives. In this section, we first provide a detailed summary of our survey and descriptive statistics of the survey results, and then describe our modeling approach for estimating the statistical relationships between pricing strategy choice and its determinants for several types of pricing strategies. We then present and discuss the results of our estimation and conclude by discussing some directions for future research.

4.1 Survey and descriptive statistics

In the survey, the respondents were first asked to name one primary product sold by their firm in the domestic market, provide some background information about the product, and answer all remaining questions in the survey with reference to only the named product. Information on the pricing strategies adopted for this product was then collected by asking the respondents to select up to five strategies from a given list of pricing strategies and to indicate the relative percentage importance of each selected strategy such that the total importance across all selected strategies summed to 100 percent. Next, the respondents were presented with a list of possible pricing objectives that their firm may seek to accomplish by adopting the selected pricing strategies and asked to rate the importance of each objective on a five-point scale. Following that, the respondents were presented with the list of pricing strategy determinants that may play a part in determining the kinds of pricing strategies adopted by the firm and asked to rate the degree to which each condition affects the pricing strategies adopted. Finally, the respondents were asked to provide some information on the profile of the firm and their professional experience.

Product profile The product information collected in the survey included the name of the product, the price of a unit of the product, the type of product (service or physical product), its stage in the PLC, the price of the product relative to the market, and whether the product was sold to businesses, end-consumers, or both. About 72 percent of the responses obtained were based on physical products, while the rest were based on service products such as financial services or business consultancy services. The products were mostly in the growth (37 percent) or maturity (54 percent) stages of the PLC, although these figures differed somewhat across countries. In terms of the price of the product

Table 1.3 Product profile (all figures in percentages)

	USA	Singapore	India	Full sample
Product type (% physical product)	60.3	68.5	87.5	72.4
Stage of the product life cycle				
Introduction	9.6	9.3	4.2	7.5
Growth	34.2	22.2	50.0	36.7
Maturity	54.8	66.7	43.1	53.8
Decline	1.4	1.9	2.8	2.0
Mean price of product relative to the market*	3.60	3.80	3.66	3.67
Product user				
Individual consumers or households	32.9	27.8	31.9	31.2
Businesses or organizations	42.5	44.4	26.4	37.2
Both	24.7	27.8	41.7	31.7

Note: * Price relative to market: 1 = 5% or more below the market; 2 = 1 to 4% below the market; 3 = same as the market; 4 = 1 to 4% above the market; and 5 = 5% or more above the market.

relative to the market, on a five-point scale where 1 = 5 percent or more below the market, 3 = same as the market, and 5 = 5 percent or more above the market, the sample mean was 3.67, suggesting that most of the products were priced at the same level as or slightly higher than the market. This phenomenon was consistent across all three countries, and the products concerned were distributed fairly evenly among consumer and business markets. Table 1.3 presents a summary of the product profiles.

Pricing strategies Each respondent was presented with the list of 19 pricing strategies encompassing a variety of pricing situations. The respondent was asked to select up to five pricing strategies from the list and to indicate the relative importance of each selected strategy such that they summed to 100 percent. For the sample as a whole, the most frequently used pricing strategy was cost-plus pricing (47.2 percent of firms), with a mean percentage importance of 37.8 percent. This was followed by price signaling (37.7 percent of firms, mean importance of 22.6 percent), perceived value pricing (34.2 percent of firms, mean importance of 33.1 percent), and parity pricing (31.7 percent of firms, mean importance of 36.9 percent). The least frequently used pricing strategies were Internet pricing (3 percent of firms, mean importance of 12.5 percent) and both break-even pricing (7.5 percent of firms, mean importance of 24.7 percent) and second market discounting (7.5 percent of firms, mean importance of 20 percent). In some cases, the frequency of usage and mean importance of certain pricing strategies varied considerably across countries. For example, only 9.7 percent of firms in India used perceived value pricing, while the figure was 52.1 percent in the USA and 42.6 percent in Singapore (the mean importance of perceived value pricing among firms that use this strategy, however, was fairly similar across countries and ranged from about 28 percent to 34 percent). Similarly, almost 42 percent of firms in India used parity pricing (mean importance of 43.2 percent), while

Table 1.4a Usage frequency (percentage of firms) and mean percentage importance of pricing strategies

Pricing strategy	Usage frequency (%)				Mean importance (%)			
	USA	S'pore	India	Full sample	USA	S'pore	India	Full sample
1. Price skimming	13.7	16.7	13.9	14.6	22.5	32.8	21.5	25.3
2. Penetration pricing	8.2	18.5	12.5	12.6	25.8	23.0	33.3	27.4
3. Experience curve pricing	12.3	9.3	11.1	11.1	21.1	32.0	30.6	27.0
4. Leader pricing	12.3	13.0	36.1	21.1	35.0	17.1	32.5	30.5
5. Parity pricing	23.3	29.6	41.7	31.7	35.5	26.6	43.2	36.9
6. Low-price supplier	5.5	9.3	6.9	7.0	27.5	28.0	32.0	29.3
7. Complementary product pricing	11.0	7.4	5.6	8.0	27.5	17.5	15.0	21.9
8. Price bundling	16.4	20.4	8.3	14.6	26.3	27.2	20.5	25.4
9. Customer value pricing	12.3	18.5	15.3	15.1	15.0	25.0	22.7	21.2
10. Cost-plus pricing	46.6	42.6	51.4	47.2	41.5	35.1	35.9	37.8
11. Break-even pricing	6.8	7.4	8.3	7.5	23.0	22.5	27.5	24.7
12. Price signaling	31.5	48.1	36.1	37.7	21.1	26.5	20.0	22.6
13. Image pricing	2.7	9.3	5.6	5.5	10.0	14.0	22.5	16.4
14. Premium pricing	31.5	24.1	29.2	28.6	24.9	21.5	22.6	23.3
15. Second market discounting	4.1	5.6	12.5	7.5	18.3	20.0	20.6	20.0
16. Periodic or random discounts	16.4	22.2	13.9	17.1	23.3	20.8	16.0	20.3
17. Geographic pricing	13.7	16.7	26.4	19.1	17.8	21.1	18.4	18.9
18. Perceived value pricing	52.1	42.6	9.7	34.2	34.3	32.8	27.9	33.1
19. Internet pricing	2.7	7.4	0.0	3.0	7.5	15.0	0.0	12.5
20. Other pricing strategies	15.1	5.6	6.9	9.5	54.3	53.3	47.0	52.2

Notes: The above table may be read as follows. As an example, consider price skimming. The column under 'USA usage frequency' shows that 13.7% of the US firms in the sample employ price skimming. Similarly, 16.7% of the Singaporean firms, 13.9% of the Indian firms and 14.6% of all the firms in the sample use price skimming. The column under 'USA mean importance' shows that on average, an importance rating of 22.5% is allocated to price skimming among US firms adopting this strategy (relative to any other pricing strategies that these firms also adopt). Likewise, the mean importance rating for price skimming is 32.8% for Singaporean firms, 21.5% for Indian firms and 25.3% for all firms in the sample employing this strategy. The percentages in each column do not add up to 100% because each firm can select between one to five different pricing strategies.

only about 30 percent of Singapore firms and 23 percent of US firms adopted this pricing strategy (with mean importance of 26.6 percent and 35.5 percent respectively). Detailed information on the usage frequency and mean importance of each pricing strategy are provided in Table 1.4a.

Table 1.4b shows the number (and percentage) of pricing strategies adopted (ranging

Table 1.4b Frequency and percentage of firms using multiple strategies

	USA	S'pore	India	Full sample
No. of firms employing 1 pricing strategy	5 (6.8%)	1 (1.9%)	3 (4.2%)	9 (4.5%)
No. of firms employing 2 pricing strategies	11 (15.1%)	9 (16.7%)	18 (25.0%)	38 (19.1%)
No. of firms employing 3 pricing strategies	20 (27.4%)	14 (25.9%)	13 (18.1%)	47 (23.6%)
No. of firms employing 4 pricing strategies	22 (30.1%)	13 (24.1%)	22 (30.6%)	57 (28.6%)
No. of firms employing 5 (or more) pricing strategies	15 (20.5%)	17 (31.5%)	16 (22.2%)	48 (24.1%)
Total	73 (100%)	54 (100%)	72 (100%)	199 (100%)

Note: * Figures in parentheses show the percentage of firms employing the stated number of pricing strategies as a percentage of the total for that column.

from one strategy up to five or more) by the firms in each country and across the entire sample. Less than 5 percent of firms in the sample employ only one pricing strategy, and indeed, more than half the firms in the sample employ at least four different pricing strategies for the (same) product which they were asked to consider in the survey.

Besides choosing from the given list of pricing strategies, the respondents were also given an option to describe any additional strategies used by their firm that were not part of the given list (about 10 percent of respondents provided such information, with these strategies having a mean importance of 52.2 percent). These strategies included strategies such as contract pricing (where a fixed price for a certain quantity of purchase is agreed upon between the firm and the customer), customer segment pricing (where prices charged depend on the profile or characteristics of the customer), channel member pricing (where prices depend on recommendations or requirements put forth by the firm's distributors in the supply chain), and regulatory pricing (where prices are controlled by the government).

In addition, the respondents were asked if the increase in Internet usage among both consumers and businesses over the last several years has affected their firms' pricing decisions and if their firms have developed any new pricing strategies as a result of this increase. On the whole, the pricing decisions of 16.2 percent of the firms have been affected by the increase in Internet usage. Most of these firms came from Singapore (29.6 percent of firms) compared to 16.7 percent of firms in the USA and 5.6 percent of firms in India. Overall, about 9 percent of firms have developed new pricing strategies due to the increase in Internet usage. Most of these firms came from the USA and Singapore, where about 13 percent of firms reported having developed new pricing strategies, compared to about 3 percent in India.

Pricing objectives To better understand the role of pricing objectives in the firm's choice of pricing strategy, the respondents were presented with a list of 17 possible objectives and asked to rate the importance of achieving each objective with regard to the most

Table 1.5 Mean ratings of importance of pricing objectives (1 = not at all important, 5 = extremely important)

Pricing objectives	US mean importance	Singapore mean importance	India mean importance	Full sample mean importance
1. Increase or maintain market share	4.21	4.02	4.15	4.14
2. Increase or maintain sales volume	4.16	4.17	4.14	4.16
3. Project a desired product image	3.57	3.96	3.21	3.55
4. Match competitor pricing	2.85	3.19	3.07	3.02
5. Increase or maintain money gross profit	3.72	4.02	3.86	3.85
6. Maintain level of competition	3.42	3.54	3.18	3.36
7. Avoid price wars	2.50	3.09	2.65	2.72
8. Increase or maintain sales revenue	4.12	4.00	3.72	3.94
9. Maintain distributor support	2.69	2.94	2.60	2.72
10. Increase or maintain gross profit margin	3.88	4.15	3.88	3.95
11. Achieve rational price structure	3.06	3.33	2.93	3.09
12. Erect or maintain barriers to entry	2.28	2.54	2.28	2.35
13. Increase or maintain liquidity	2.21	2.48	2.46	2.37
14. Undercut competitor pricing	1.97	1.98	1.94	1.96
15. Avoid government attention or intervention	1.47	1.94	1.74	1.70
16. Avoid customer complaints about unfair prices	2.11	2.61	2.43	2.36
17. Cover costs	3.57	3.69	3.44	3.56

important pricing strategy they have selected on a five-point scale where 1 represents 'not at all important' and 5 represents 'extremely important'. For the sample as a whole, the most important objectives were those of increasing or maintaining market share (mean importance rating of 4.14) and increasing or maintaining sales volume (mean importance rating of 4.16). These were followed by the objectives of increasing or maintaining gross profit margin (mean importance rating of 3.95) and that of increasing or maintaining sales revenue (mean importance rating of 3.94). The least important objectives were those of avoiding government attention or intervention and undercutting competitor pricing (mean importance rating of 1.70 and 1.96 respectively). The complete list of objectives and the importance ratings of each pricing objective for each country and for the sample as a whole are given in Table 1.5.

Pricing strategy determinants To examine the role of various pricing strategy determinants (expressed in the form of company and product conditions, market and customer conditions, and competitive conditions) in influencing choice of pricing strategy, the respondents were asked to rate the level or intensity of these conditions with regard to

the named product. Company and product determinants included the age of the product, issues relating to product design, production costs and capacity utilization, the firm's market share and coverage, the profitability of accompanying and supplementary sales, and the number of intermediaries in the supply chain. Market and customer determinants of pricing strategies included the sensitivity of the firm's customers to price differences between brands, sensitivity of market demand to changes in average price, ease of determining market demand, market growth rate, customer costs and legal constraints. Competitive determinants included the degree of product differentiation between brands, the ease of detecting competitive price changes, and market share concentration of the leading firms in the industry. Table 1.6 presents a summary of the respondents' mean ratings of these pricing strategy determinants, together with the appropriate rating scales.

Table 1.6 Mean ratings of pricing strategy determinants

Pricing strategy determinants	Rating scale	USA	S'pore	India	Full sample
Market conditions					
1. Sensitivity of customers to price differences between brands	1 = Insensitive, 7 = Sensitive	4.92	4.85	4.66	4.81
2. Sensitivity of market demand to changes in average price	1 = Insensitive, 7 = Sensitive	3.85	4.54	4.00	4.09
3. Ease of determining market demand	1 = Difficult, 7 = Easy	3.86	4.04	4.34	4.08
4. Market growth rate	1 = Low, 7 = High	3.92	4.00	4.54	4.16
5. Customer switching costs	1 = Low, 7 = High	3.21	3.94	3.65	3.56
6. Customer search costs	1 = Low, 7 = High	3.21	3.68	3.06	3.28
7. Customer transaction costs	1 = Low, 7 = High	2.96	3.47	3.21	3.18
8. Impact of the Internet on market demand	1 = Low, 7 = High	2.15	2.48	1.38	1.98
9. Legal constraints	1 = Low, 7 = High	2.48	2.28	2.06	2.27
Competitive conditions					
10. Ease of detecting competitive price changes	1 = Difficult, 7 = Easy	4.82	4.50	5.12	4.84
11. Market share concentration of the top three firms in the industry	1 = Less than 5%, 7 = Greater than 80%	5.04	5.09	5.40	5.19
12. Product differentiation between brands	1 = Low, 7 = High	4.08	4.09	3.62	3.92
13. Impact of the Internet on competitive conditions	1 = Low, 7 = High	2.37	2.68	1.42	2.13
Product/company conditions					
14. Estimated age of product in years		7.28	7.61	8.45	7.79
15. Cost disadvantage due to experience curve	Percentage of firms	34.2%	27.8%	43.1%	35.6%

Table 1.6 (continued)

Pricing strategy determinants	Rating scale	USA	S'pore	India	Full sample
16. Cost disadvantage due to economies of scale	Percentage of firms	35.9%	33.3%	47.2%	39.4%
17. Capacity utilization (relative to other products)	1 = Low, 7 = High	4.75	4.71	5.37	4.96
18. Costs (relative to competitors)	1 = Disadvantage 7 = Advantage	4.15	4.28	4.21	4.21
19. Major product change (significance of most current design change)	Percentage of firms	21.4%	20.4%	13.9%	18.2%
20. Market coverage	Percentage of firms serving only one customer segment	8.2%	9.3%	2.8%	6.5%
21. Market share	1 = Low, 7 = High	5.19	5.04	5.59	5.29
22. Per sale/contract pricing	1 = Low, 7 = High	0.53	0.57	0.38	0.49
23. Profitability of accompanying sales	1 = Low, 7 = High	4.34	4.15	3.26	3.89
24. Profitability of supplementary sales	1 = Low, 7 = High	3.15	3.53	2.64	3.06
25. Number of intermediaries in supply chain	1 = Low, 7 = High	2.92	2.69	2.81	2.81
26. Costs of developing the product	1 = Low, 7 = High	4.25	4.22	4.48	4.28
27. Impact of the Internet on product/company conditions	1 = Low, 7 = High	2.73	2.98	1.47	2.34

In terms of market and customer determinants of pricing strategy, the results suggest that customers are fairly sensitive to price differences between brands as well as to changes in the average price. The former is particularly true in the USA and Singapore, possibly due to the higher number of alternative brands available to customers in these highly developed markets, while the latter is especially so for Singapore, due to the small and concentrated nature of its market. All three markets appear to have a moderate growth rate. Customer costs (switching, search and transaction costs) are moderately low across all three markets. Finally, both the impact of the increase in Internet usage on market demand as well as legal constraints on pricing strategies appear to be rather low as well, suggesting, for the former, that most customers still employ traditional methods of shopping and purchase, and, for the latter, that government regulations on pricing are not too restrictive.

The ratings for the competitive determinants of pricing strategy suggest that it is fairly easy for the firms surveyed to detect competitive price changes in the market. Additionally, oligopolistic competition seems to prevail across all three countries, with the top three firms in various industries commanding (in total) more than half the market share in the industry. Product differentiation between brands appears to be moderate

and, as before, the impact of the Internet on the competitive conditions faced by the firms appears to be low.

Finally, in terms of the company and product determinants of pricing strategy, the ratings across firms in all three markets appear to be moderate and quite similar across countries, with a couple of exceptions. The first pertains to the frequency of a major product change – more than 20 percent of firms in the USA and Singapore report having made a significant change in their current product design while the figure is about 14 percent for India. The second pertains to market coverage: the products marketed by the Indian firms tend to serve multiple customer segments, with only 2.8 percent of Indian firms reporting that they serve only one segment, *vis-à-vis* 8.2 percent and 9.3 percent for firms in the USA and Singapore respectively.

Profile of firms and respondents The firms from which the survey responses were obtained cover a diverse range of industries and product categories. They also ranged from small-scale businesses with fewer than ten employees and annual revenues of less than $10 million to large, multinational corporations with several hundred thousand employees and billions of dollars in revenue. Most of the respondents surveyed were middle or senior managers who have had a significant number of years of managerial experience (average of 11.1 years) and have been employed in their present position for a considerable period of time (average of 4.5 years). In addition, most respondents have a fairly high degree of involvement in their firm's pricing decisions, with an average involvement rating of 5.45 on a seven-point scale where 1 represents 'not involved at all' and 7 represents 'strongly involved'. Detailed descriptive statistics on the profile of the firms and respondents are available from the authors.

4.2 Data analysis and discussion

We examined the relationship between the firms' choice of pricing strategies, pricing objectives and pricing strategy determinants by carrying out binary logistic regressions with the choice of the pricing strategy as the dependent variable and relevant variables representing the objectives, determinants, as well as firm and respondent characteristics as the explanatory variables. This section describes our data analysis procedure and its results.

Modeling approach and estimation Given that we collected a large number of variables in the study, we used factor analysis to see if the cumulative set of variables could be reduced to a smaller set of orthogonal factors, which would then be used to estimate the binary choice models for the different pricing strategies. The factor analysis was conducted separately on the groups of variables representing the pricing objectives, the pricing strategy, determinants, as well as the characteristics of the firm and the respondent.

The factor analysis for the 17 variables representing pricing objectives was relatively straightforward. The results shown in Table 1.7 indicate that the 17 objectives can be grouped into nine composite objectives, which explains 78.8 percent of the variance in the data.

The survey had outlined 27 possible determinants of pricing strategy that may influence a firm's choice of pricing strategies, broadly classified under three categories of business conditions: company and product conditions, market and customer conditions, and

Table 1.7 Factor analysis of the pricing objectives

Pricing objective	Factor loading	Name for the factor
1. Increase or maintain market share	0.79	Increase or maintain market share
2. Increase or maintain sales volume	0.85	
3. Increase or maintain sales revenue	0.73	
4. Increase or maintain gross profit dollars	0.83	Increase or maintain profit
5. Increase or maintain gross profit margin	0.86	
6. Cover costs	0.52	
7. Match competitor pricing	0.70	Competitor-based pricing
8. Undercut competitor pricing	0.84	
9. Achieve rational price structure	0.82	Rational pricing
10. Increase or maintain liquidity	0.58	
11. Maintain level of competition	0.50	Maintain competitive level
12. Avoid price wars	0.85	
13. Avoid government attention or intervention	0.62	Avoid government attention
14. Avoid customer complaints about unfair prices	0.88	
15. Erect or maintain barriers to entry	0.82	Erect or maintain barriers to entry
16. Maintain distributor support	0.87	Maintain distributor support
17. Project a desired product image	0.96	Project desired product image

competitive conditions. The results of the factor analysis on the 27 variables are shown in Table 1.8, and enabled us to simplify the set of 27 measured variables into 12 factors, which explains 77.4 percent of the variance in the original variables. All but two of the factor loadings are in the expected direction.

In addition to pricing objectives and determinants relating to the business conditions under which the firms are operating, specific demographic characteristics of the survey respondent and the firm may also play a part in affecting the choice of pricing strategy. To account for the effect of such respondent characteristics, we used the size of the firm and the degree of involvement of the respondent with the firm's pricing decisions as two other explanatory variables in the choice model. As with the pricing objectives and determinants, these two variables were based on a factor analysis of the demographic measures we collected in the survey.

The net result of the variable reduction exercise yielded 23 variables[3] (that affect choice of pricing strategy) for the choice model, and is summarized in Table 1.9. In addition, we included two dummy variables to take account of the country differences among the three countries; one dummy variable to represent US respondents and one to represent Singapore respondents.

[3] We use variables directly rather than factor scores to retain the specific meaning of the determinants of pricing strategies and ease of interpretation.

Table 1.8 Factor analysis of the measured pricing strategy determinants

Pricing determinants	Factor loading	Name for the factor
1. Impact of Internet on competitive conditions faced by firm	0.93	Impact of the Internet
2. Impact of Internet on market demand	0.90	
3. Impact of Internet on product/company conditions faced by your firm	0.80	
4. Customer switching costs	0.80	Customer costs
5. Customer search costs	0.76	
6. Customer transaction costs	0.76	
7. Cost disadvantage due to experience curve	0.92	Cost disadvantages
8. Cost disadvantage due to economies of scale	0.91	
9. Profitability of accompanying sales	0.84	Other sources of profit
10. Profitability of supplementary sales	0.74	
11. Sensitivity of customers to price differences between brands	0.79	Customer price sensitivity
12. Sensitivity of market demand to changes in average price	0.78	
13. Legal constraints	0.36	
14. Per sale/contract pricing	0.38	
15. Capacity utilization (relative to other products)	0.74	Capacity utilization
16. Age of product in years	0.64	
17. Costs relative to competitors	0.58	
18. Market share	0.69	Market share
19. Market share concentration of top three firms in the industry	0.68	
20. Ease of detecting competitive price changes	0.52	
21. Number of intermediaries in the supply chain	0.39	Intermediaries in the supply chain
22. Product differentiation between brands	−0.44	Product differentiation
23. Major product change	0.79	
24. Costs of developing the product	0.39	Market development costs
25. Market coverage	0.89	
26. Market growth rate	0.89	Market growth rate
27. Ease of determining market demand	0.60	Market demand determination

Our study examined a list of 19 possible pricing strategies, and we focused our analysis on six of the most important strategies as chosen by the respondents. We first selected the specific pricing strategy deemed by each respondent as the one with largest importance (out of possible five strategies that could be indicated by the respondent) for the product in question. We then identified the following six strategies that are most frequent with this criterion; the frequencies of these six strategies are: 53 for cost-plus pricing, 35 for

Table 1.9 Summary of the various factors affecting the choice of pricing strategy

Category	Factors
Pricing objectives	Increase or maintain market share
	Increase or maintain profit
	Competitor-based pricing
	Rational pricing
	Maintain competitive level
	Avoid government attention
	Erect or maintain barriers to entry
	Maintain distributor support
	Project desired product image
Pricing strategy determinants	*Company and product factors*
	Cost disadvantages
	Other sources of profit
	Capacity utilization
	Intermediaries in the supply chain
	Market and customer factors
	Impact of the Internet
	Customer costs
	Customer price sensitivity
	Market development costs
	Market growth
	Market demand determination
	Competitive factors
	Market share
	Product differentiation
Respondent characteristics	Firm size (number of employees)
	Degree of involvement in pricing

perceived value pricing, 34 for parity pricing, 16 for price signaling, and 14 each for premium pricing and leader pricing. We estimated the choice model in the form of binary logistic regressions for each of the six pricing strategies. Based on the factor analyses done above, there were 25 independent variables: 9 variables were for the objectives of pricing strategies, 12 for the determinants of strategy, 2 country variables and 1 variable each for the size of the firm and the degree of involvement of the respondent. The logistic regression model was run with all the 25 variables. Consequently, even variables that are not significant were a part of the model.

Results and discussion The estimated coefficients for the six pricing strategies are given in Table 1.10. This section discusses the estimation results and the observed relationship between the key elements of the pricing decision.

COST-PLUS PRICING Cost-plus pricing refers to the pricing of a product at a predetermined margin over the product's estimated production costs. Although it is historically a commonly used pricing method, critics have warned against the viability of cost-plus pricing as a profitable pricing strategy because not only does it ignore the customer's valuation of

Table 1.10 Estimated logistic regression coefficients for six pricing strategies

Variable name	Cost-plus pricing	Perceived value pricing	Parity pricing	Price signaling	Premium pricing	Leader pricing
Country – USA	0.211	**1.882***	**−25.397***	−0.199	**2.497**	0.165
Country – Singapore	0.398	**2.417***	**−2.178***	1.390	**3.072**	−23.794
Pricing objectives						
Increase or maintain market share	0.049	0.122	0.152	−0.011	**−0.506***	**−0.454**
Increase or maintain profit	**0.473***	−0.100	**−0.180***	0.017	0.083	**−0.541***
Competitor-based pricing	0.089	**−0.307***	**0.290***	**−0.410**	**−0.657***	−0.212
Rational pricing	**0.213***	−0.116	0.109	−0.194	**−0.615***	0.072
Maintain competitive level	−0.161	−0.075	**0.337***	**0.680***	0.443	−0.557
Avoid government attention	0.097	0.044	−0.135	−0.104	0.395	**1.008***
Erect or maintain barriers to entry	**−0.384***	**0.409***	**0.016***	0.092	−0.181	−0.232
Maintain distributor support	0.038	0.042	**0.027***	**−0.702***	**0.858**	−0.443
Project desired product image	**−0.356***	0.294	−0.194	0.484	**0.957***	**2.716***
Pricing strategy determinants						
Impact of the Internet	−0.030	−0.038	**0.308***	**0.112**	**−0.380***	−0.571
Customer costs	0.041	−0.060	**0.597***	−0.074	**−0.347***	**−0.473***
Cost disadvantages	**−0.274**	0.053	**1.193**	**−0.733***	−0.200	**1.606***
Other sources of profit	−0.028	−0.032	−0.166	0.001	0.211	0.158
Customer price sensitivity	0.016	−0.032	**1.181***	0.043	0.131	−0.190
Capacity utilization	−0.040	−0.033	−0.129	**0.248**	**−0.271**	0.100
Market share	0.034	−0.046	−0.028	0.199	−0.088	**1.476***
Intermediaries in the supply chain	**−0.231***	−0.035	−0.252	0.157	−0.058	**1.397***
Product differentiation	**0.244***	0.097	−0.483	**0.531***	−0.091	**−1.377***
Market development costs	−0.047	0.055	**0.262**	0.033	0.157	0.018
Market growth rate	0.011	−0.178	0.249	−0.204	**1.378***	0.801
Market demand determination	0.048	**0.228**	0.490	0.262	−0.379	0.137
Respondent and firm characteristics						
Firm size (number of employees)	**0.189***	0.074	**0.000**	−0.192	**0.634***	**−0.924***
Degree of involvement in pricing	**−0.212***	**0.107**	−0.009	0.045	**0.280**	0.053
Constant	**−4.828***	**−4.433***	**−3.696***	**−9.881***	**−9.200***	**−16.727***

Table 1.10 (continued)

Variable name	Cost-plus pricing	Perceived value pricing	Parity pricing	Price signaling	Premium pricing	Leader pricing
Number of observations	199	199	199	199	199	199
2lnL (negative)	168.222	139.532	123.172	68.128	48.268	37.936
Cox & Snell R-square	0.269	0.205	0.256	0.195	0.234	0.273
Hosmer–Lemeshow Chi Square (8 df)	8.867	NA	15.491	26.191	4.619	3.788
Percent correct predictions	79.9	82.9	82.8	93.5	95.5	93.0
Number selecting this strategy	53	35	34	16	14	14

Notes: Values in bold are significant at 0.20 or below.
Values in bold with an asterisk (*) are significant at 0.10 or below.

the product, it may in fact harm profitability by overpricing the product in weak markets and underpricing it when demand is strong. In fact, some researchers argue that using a product's cost to determine its price does not make sense because it is impossible to determine a product's unit cost accurately without first knowing its sales volume (which depends on price), and thus cost-plus pricers are 'forced to make the absurd assumption that they can set price without affecting volume' (Nagle and Hogan, 2006, p. 3). Nevertheless, the results of the present study suggest that it is in fact the most popular pricing strategy used by firms across different industries and countries.

In adopting cost-plus pricing, the estimation results show that the most significant pricing objectives are to increase or maintain profit and to maintain a rational pricing structure. Indeed, one of the key reasons behind the popularity of cost-plus pricing is that it brings with it an air of financial prudence. It is a conservative approach that balances risks and returns by seeking to achieve an acceptable level of financial viability rather than maximum profitability. However, cost-plus pricing tends to go against a firm's objective of erecting or maintaining barriers to entry and maintaining a desired product image. It is difficult for an incumbent to price low enough to deter new entrants if it needs to achieve a predetermined margin over its estimated production costs, and since it is a pricing strategy that accounts for only the firm's supply constraints and fails to consider the customer's perception of the product, it will be difficult to use it to influence the product's image in the customer mindset.

In terms of the pricing strategy determinants, the firm's cost disadvantages have a significant and negative impact on the choice of a cost-plus pricing strategy. This result appears counter-intuitive at first, since the higher a firm's estimated costs of production, the more necessary it will be to cover these costs adequately and, hence, the more one would expect the firm to adopt the cost-plus method. However, as shown in Table 1.4b, most firms use multiple pricing strategies even for the same product. It is likely that the firms are trying to find an optimal balance between cost-plus pricing and other methods that take into account other issues besides costs, particularly when cost-plus pricing

on its own leads to unreasonably high and uncompetitive prices. Next, the greater the number of intermediaries in the firm's supply chain, the less likely the firm is to adopt cost-plus pricing. This is because more intermediaries not only leads to more cost disadvantages, but also results in reduced pricing control for the firm with regard to the final price charged to consumers, making it more difficult for the firm to specify a target profit margin for its product. On the other hand, a high level of product differentiation increases the likelihood of a firm adopting cost-plus pricing. This is because competitive pricing pressures are reduced for a unique product, enabling the firm to set a price that is commensurate with the product's costs.

Finally, in terms of respondent and firm characteristics, larger firms are more likely to adopt cost-plus pricing, while the lower the survey respondent's degree of involvement with the pricing decision, the more likely the firm is to adopt this strategy. This may be because larger firms are more likely to have established pricing policies and cost-plus calculation methods in place, developed by their accounting and finance departments, which specify minimum pricing requirements above estimated production costs in order to achieve a certain projected return. In view of these policies, marketing managers are likely to have less flexibility over pricing decisions. As for the country-specific effects, the coefficients on the country dummies suggest no significant difference in a firm's likelihood of adopting cost-plus pricing across the three countries considered, which makes sense given its popularity as a pricing method.

PERCEIVED VALUE PRICING Perceived value pricing, the next most frequently used pricing strategy, refers to the practice of pricing the product in accordance with what customers perceive the product to be worth. It is a customer-centric approach to pricing that prioritizes the customer's product valuation above cost, competition and other considerations.

Looking at the coefficients for pricing objectives, we observe that competitor-based pricing has a negative relationship with the likelihood of adopting perceived value pricing. This is because the more a firm looks toward the customer in its pricing decisions, the less concerned it is about competitive pricing pressures. Next, the more a firm wants to stop new players from entering the market, the more likely it is to adopt perceived value pricing. Customers who believe that they are getting value for money are more likely to remain loyal to incumbent firms and will hence make the market less attractive for new entrants. Finally, it is interesting to note that maintaining a desired product image does not significantly affect the likelihood of adopting perceived value pricing. An explanation for this could be that product image does not necessarily have to do with a product's value or quality. For instance, in the automobile market, Volvo consistently projects an image of safety, while in the digital music player market, the Apple iPod projects a hip, cool and user-friendly image. In both cases, however, the desired image was established less through the respective firms' pricing strategies and more through consistent and effective advertising messages, word of mouth, and other non-price methods. In other words, a good product image does not necessarily imply an expensive or exclusive product.

In terms of the pricing strategy determinants, the easier it is to determine the market demand, the more likely it is for a firm to use perceived value pricing. No other determinants are observed to significantly affect the likelihood of adopting perceived value pricing. When firms know where their customers come from and are more confident

about their projected sales figures, they can more easily set a price that is more acceptable to customers and at the same time minimizes risks to profitability. Accordingly, in terms of respondent characteristics, the higher the degree of involvement of the respondent with the pricing decision, the more likely it is for the firm to practice perceived value pricing, since this method requires a more flexible approach to pricing. Finally, the results show the presence of significant country-specific effects for perceived value pricing. Firms operating in the USA appear most likely to adopt this method, followed by Singapore and then India.

PARITY PRICING Parity pricing refers to the practice of setting a price for the product that is comparable to that of the market leader or price leader. In the former case, it means pricing the product close to the prices set by the biggest player(s) in the industry (which may or may not be the lowest or highest price on the market). In the latter case, it means pricing the product close to the prices set by the lowest-price players on the market. It is a strategy that takes into account competitive pricing pressures more than other factors.

Looking at the coefficients on the pricing objective variables, we see that all three objectives that involve meeting competitive pricing pressures (competitor-based pricing, maintaining competitive level, and erecting or maintaining barriers to entry) have a positive relationship with a firm's likelihood of employing parity pricing, which is in line with expectations. Next, the desire to maintain distributor support also increases a firm's likelihood of using parity pricing. This is because in competitive markets, distributors are just as likely as customers to switch to a different supplier if the latter presents them with an opportunity to earn higher margins. Hence it is important for a firm to ensure that its distributors earn competitive margins, and one way of doing this (and demonstrating it to distributors) is by making sure that the (end-user) price of its product is comparable with those of other competing suppliers. Finally, the more a firm wants to increase or maintain its profit, the less likely it is to adopt parity pricing. This is also intuitively reasonable because, in this case, the firm is more concerned with setting prices that are comparable with the competition instead of maintaining or maximizing the product's profitability.

A number of pricing strategy determinants have a positive relationship with a firm's likelihood of using parity pricing. First, the higher the impact of the Internet on the firm's operating and business conditions, the more likely it is to adopt parity pricing. The exponential growth in global Internet usage over the last decade has greatly facilitated the flow of market information and reduced search and transaction costs for customers and distributors, making it easier for the latter to compare prices across potential suppliers. As a result, it has become more necessary for firms to price their products more competitively. Next, the higher the customer costs (in the form of search, transaction and switching costs) and the higher the customer price sensitivity, the more likely it is for a firm to practice parity pricing. The latter is self-explanatory, while the former can be explained by the notion that the more difficult it is for customers to compare or switch between suppliers, the more likely it is for firms to ignore pricing pressures from customers and focus on competitive pressures instead. In addition, high cost disadvantages and market development costs also lead to the increased likelihood of using parity pricing. This could be because firms are trying aggressively to recoup these costs and to make sure that they price in a manner that achieves a balance between per unit profitability (by pricing close

to the market leader) and market share (by pricing close to the price leader), which can be more profitable in the long run than pricing at either extreme.

The estimation results also show that, in general, firms in India are most likely to adopt parity pricing, followed by firms in Singapore and then the USA. However, specific respondent and firm characteristics do not appear to have a significant impact on the likelihood of this strategy being adopted.

PRICE SIGNALING Price signaling is the strategy of using price as an indicator to customers of the product's quality. Although other product attributes (such as brand name) may also influence customers' perceptions of a product's quality, price appears to be particularly influential, and most customers assume that price and quality are positively correlated. Accordingly, price signaling is one of the most popular pricing strategies that firms employ, as not only does it improve customers' quality perceptions of its product, the higher price also translates into larger margins. Like perceived value pricing, it is a customer-centric pricing strategy that focuses more on customers' product perceptions than on other factors.

The only significant pricing objective that increases a firm's likelihood of adopting price signaling appears to be maintaining the level of competition. Since the goal of price signaling is to communicate the quality of your product *vis-à-vis* the competition, it often involves setting a price that is comparable with (if not higher than) than the prices of competing products, thereby maintaining (or reducing) the level of competition and reducing the likelihood of a price war. In the same vein, having competitor-based pricing as a pricing objective significantly reduces the likelihood of price signaling being adopted, as does maintaining distributor support. The reason for the latter can again be attributed to the firm's focus on customers in adopting a price signaling strategy, even at the prospect of having distributors complain that a high retail price affects retail and intermediary sales. As in perceived value pricing, we note that projecting a desired image does not significantly influence the likelihood of price signaling being adopted as a strategy, and a similar reason as discussed previously may also be in effect here.

Looking at the coefficients on the pricing strategy determinants, the following variables increase the likelihood of price signaling being adopted by a firm: impact of the Internet, capacity utilization and product differentiation. As discussed under the section on parity pricing, the Internet has greatly facilitated the availability and flow of information to both firms and their customers. Many customers use the Internet to search for product information prior to purchase, and it serves as an efficient and cost-effective medium for firms to practice price signaling.[4] As for product differentiation, it is reasonable to postulate that firms that use price as an indicator of their product's quality typically have products that are quite differentiated from their competitors (or at least perceived to be so by the firm's customers), thereby justifying the higher relative price. Next, the capacity

[4] Many customers also use the Internet to seek low prices, and this may seem to run contrary to firms' use of price signaling via the Internet to indicate the quality of their product. One explanation could be that firms that use price signaling on the Internet are those whose products are differentiated enough in terms of perceived quality to warrant a price signaling strategy, or those who have a product line, with some lower-quality products priced competitively and others (targeted at the less price-conscious customers) priced relatively higher.

utilization variable encompasses not only how much the product in question makes use of the firm's available production capacity relative to its other products, but also the age of the product and the costs of the product relative to the firm's competitors. The positive coefficient on the variable can thus be explained by the notion that the more the firm has invested in a product, in terms of both time and production costs, the more likely the product is in fact of considerably higher quality than alternative products and, hence, the more likely the firm is to use price signaling to communicate this quality to customers. In further support of this observation, the coefficient on the cost disadvantages variable is negative, indicating that the fewer cost disadvantages the firm has, the more likely it is to produce a better product, which in turn makes it more likely to adopt price signaling.

Finally, the estimation results suggest that firms in all the three countries where the survey was performed are equally likely to use price signaling. Similarly, specific firm and respondent characteristics do not appear to significantly influence the probability that a firm will adopt this strategy.

PREMIUM PRICING Premium pricing is the strategy of pricing one version of a firm's product at a premium, offering more features than are available on the firm's other products. It is a strategy employed by firms that have multiple versions of the same product along a product line, with each version targeted at different customer segments.

We note first that both country-specific effects and respondent and firm characteristics are significant in influencing the likelihood of adopting this strategy. Firms in Singapore are more likely to adopt premium pricing, followed by the USA and India. Larger firms also have a higher likelihood of using this strategy, which makes intuitive sense because larger firms are more likely to have different versions of their product(s) for sale. Likewise, the respondent's degree of involvement in the pricing decision also has a significant and positive impact on the firm's likelihood of using premium pricing.

The following pricing objectives have a negative impact on the likelihood of a firm employing premium pricing: increasing or maintaining market share, competitor-based pricing and rational pricing. Since premium pricing is targeted at customers who value feature-laden products and are generally quite willing to pay a premium for them, firms that use this strategy are less likely to focus on market share or competitive pricing issues, at least not for the product in question. Conversely, maintaining distributor support and projecting a desired product image increase a firm's likelihood of adopting premium pricing. By pricing different versions of its products accordingly, instead of having a 'one-size-fits-all' average price that may overprice some products and underprice others, overall sales should improve as customers are given the flexibility to choose and pay for the value received. In addition, distributors also have the flexibility of carrying some or all of the firm's products. Hence it is likely that improved distributor support can be achieved with this pricing strategy. As for maintaining a desired product image, premium pricing can certainly help to differentiate the premium product from not only other products in the firm's product line but competing firms' products, as well, thereby contributing toward the image desired for the product.

As for the pricing strategy determinants, the following variables are observed to have a negative influence on the likelihood of premium pricing being adopted: customer costs, the impact of the Internet and capacity utilization. Interestingly, the latter two are in contrast to price signaling, which is another strategy that involves the setting of high prices.

The explanation may be as follows. In terms of the impact of the Internet, the ease of obtaining product information provided by the Internet may induce the firm's customers (even the more feature-conscious and less price-conscious ones) to explore other product options, both within the firm's product line and from competing firms, and increase the likelihood that these customers will buy an alternative product. Hence it has a negative impact on the probability of adopting premium pricing. As for capacity utilization, the observed result can be explained by the notion that the less the firm has invested in the product in terms of time and production costs, the less likely it is for the product to be feature-laden and, hence, be priced using premium pricing. Finally, the estimation results show that market growth rate has a positive impact on the likelihood of adopting premium pricing. This is because the faster the market and the firm's customer base grow, the more diverse customer tastes are likely to be. Hence it becomes more likely for firms to introduce, to suit different customers different versions of the product, at least one of which is likely to be premium-priced.

LEADER PRICING The sixth most frequently used pricing strategy is leader pricing, which refers to the practice of initiating a price change or establishing a benchmark price for a product in a category, and expecting other firms to follow. It is a pricing strategy that market leaders typically adopt, which makes its apparent popularity as a pricing strategy and the observed negative relationship between firm size and the likelihood of adopting leader pricing quite counter-intuitive. One reason for this could be that the firms in our sample are relatively small (Tables 1.7 and 1.9 show that about half the firms have annual revenues of less than $100 million and employ fewer than 500 people), suggesting that many of these firms compete in regional, local or niche markets of limited size where few or no major players dominate (as is the case in larger or global markets) and most players are of comparable footing with one another. In such markets, any price change initiated by a player is likely to be noticed by the other players. As with cost-plus pricing and price signaling, country-specific effects are not significant for leader pricing, suggesting that firms in all three countries are equally likely to adopt this pricing method.

The pricing objectives of increasing or maintaining market share, and increasing or maintaining profit, are observed to have negative relationships with the likelihood of adopting leader pricing. This is because the more competitors follow the benchmark set by the price leader, the more intense the competition and the more fragmented the market. This suggests that firms employ this strategy not as a primary strategy to enhance share or profitability, but more as a secondary strategy to be used when its primary strategies are inappropriate, such as when competition is intense and market demand is at its peak, with little room for further expansion. On the other hand, the more a firm wants to avoid government attention in its pricing decision, the more likely it is to adopt leader pricing. Similarly, leader pricing is more likely to be used when the firm wants to project a certain product image.

Lastly, in terms of the pricing strategy determinants, the observed results show that the higher the firm's market share, the more likely it is to adopt leader pricing since competitors are more likely to follow. Next, the higher the costs are to customers of buying and switching from the product (and presumably competing products), and the higher the degree of product differentiation, the less likely it is that the firm will adopt leader pricing. This may be because, under such situations, firms are less worried about competitors and

can price their products more independently of them. However, as with parity pricing, the results suggest that high cost disadvantages lead to an increased probability of adopting leader pricing. This could be because, with high costs of production, firms are more likely to set prices at a level that can cover these costs adequately and hope that its competitors will follow suit. For the same reason, the more intermediaries there are in the supply chain (which translates to a cost disadvantage), the more likely it is that a firm will use leader pricing.

5. Conclusion and future research

The foregoing empirical study has provided a current overview of the kinds of pricing strategies that firms adopt and a discussion of the various factors affecting the adoption of these strategies, across three different countries. It has also made a first attempt at studying the relationship between the three key elements of the pricing decision under an integrated framework: the pricing strategies adopted by a firm, the pricing objectives that these strategies are meant to achieve, and the strategy determinants (in the form of internal and external business conditions) that can influence the firm's choice of pricing strategies. Firms adopt different pricing strategies to achieve a variety of objectives and, contrary to popular belief, pricing to cover costs (or cost-plus pricing) is not always the dominant objective. Many pricing strategies aimed at maximizing earnings, improving customers' product perceptions and addressing competitive pressures (sometimes at the expense of share or profit) are frequently adopted to achieve other objectives. In addition to managerial objectives, the business conditions that the firm is operating under can also greatly influence the type of pricing strategy adopted. These conditions encompass both the firm's internal constraints and competencies as well as the external pressures it faces from competitors, consumers and supply chain partners. While these pricing strategy determinants often go hand in hand with the firm's pricing objectives, at times they are observed to be at odds with one another. This is because firms typically have multiple pricing objectives at any one time, and often some of these objectives are in conflict with one another (e.g. using cost-plus pricing to maintain or increase profit while using parity pricing to meet competitive pricing pressures and deter new entrants). In such a situation, firms have to find the optimal tradeoff between the various objectives and pricing strategies adopted, while taking into account the relevant pricing strategy determinants, in a way that provides the maximum overall 'benefit' to the firm. This benefit may comprise one or more of the following performance indicators: profit, market share, customer support/loyalty and distributor support, among others.

While the study has provided some new insights into the firm's pricing decisions, much further work still needs to be done, particularly to address the limitations of the present study. First, as is the case for much of managerial survey-based research, the small size of the sample used in the study, especially in each country, is an issue. Because of this limitation, the survey data had to be pooled across countries when performing the logistic regression for each pricing strategy, leaving the two country dummies as the only variables to account for country-specific effects. If more responses had been obtained and separate regressions had been performed for each country, deeper insights would have been obtained into the difference in pricing decisions across the three countries.

Next, the logistic regression models estimated in the study also pooled many industries and product types together. While the advantage of such an approach is that it

provides a general picture of how a firm (any firm in any industry) makes its pricing decision, the disadvantage is that it overlooks many interesting and critical differences in pricing decision-making that may exist across different industries. Future research can consider estimating separate models for different industries or product types. Along the same lines, various subsets of the array of pricing strategies, objectives and determinants considered may be more applicable to specific industries and products, and this would perhaps explain why many of the estimated coefficients in the regression models are non-significant. To address this limitation, more research needs to be done that first explores the applicability of various pricing strategies, objectives and determinants to various industries and products, after which a similar analysis of the relationships between these elements of the pricing decision can be done for each subset of industries and products.

Finally, while the descriptive study has provided a big picture of the relationship between the key elements of a pricing decision, more complex mathematical models can be developed to study this relationship in greater depth and under more rigorous modeling assumptions. For instance, rather than performing a binary logistic regression for each individual pricing strategy, which implicitly and somewhat unrealistically assumes that the pricing strategy choices within a firm were made independently, multinomial or multivariate pricing strategy choice models can be developed for the firms that would model the firm's strategy choice process more realistically. Other studies could incorporate game-theoretic frameworks that model the firm's optimal choice of pricing strategies, given its strategic considerations of its competitors' choices. The firm's objective function to be used in these game-theoretic models can vary from the popular profit function that is often used in game theory papers to other functions representing the many other objectives that the firm can have. The topic of price rigidity (or stickiness) warrants comprehensive econometric analyses for the US context using data collected for computing consumer price indexes and for other purposes.

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2 Willingness to pay: measurement and managerial implications

*Kamel Jedidi and Sharan Jagpal**

Abstract
Accurately measuring consumers' willingness to pay (WTP) is central to any pricing decision. This chapter attempts to synthesize the theoretical and empirical literatures on WTP. We first present the various conceptual definitions of WTP. Then, we evaluate the advantages and disadvantages of alternative methods that have been proposed for measuring it. In this analysis, we distinguish between methods based on purchase data and those based on survey/experimental data (e.g. self-stated WTP, contingent valuation, conjoint analysis and experimental auctions). Finally, using numerical examples, we illustrate how managers can use WTP measures to make key strategic decisions involving bundling, nonlinear pricing and product line pricing.

1. Introduction

Knowledge of consumers' reservation prices or willingness to pay (WTP) is central to any pricing decision.[1] A survey conducted by Anderson et al. (1993) showed that managers regard consumer WTP as 'the cornerstone of marketing strategy', particularly in the areas of product development, value audits and competitive strategy. Consider the following managerial questions you would face as a new product manager:

- How does pricing affect the demand for my new product?
- What price should I charge for my new product?
- What is the likely demand for my new product if I charge this price?
- What are the sources of demand for the new product? What fractions of this demand come from cannibalization, switching from competitors, and market expansion? And which competitors will the new product affect most?
- Which products in my product line should be bundled? And how much should I charge for the bundle and for each of its components?
- How should I determine my product mix and my product-line pricing policy?
- If I can use a one-to-one marketing strategy, how should I customize prices across consumers or consumer segments?
- How should I determine the optimal quantity discount schedule for my product?

From the perspective of the standard economic theory of consumer choice, the key to answering all these questions is knowledge of consumers' WTP for current and new product offerings in a category. Consider, for instance, a phone company that is planning to bundle its landline and wireless services. If the market researcher has information on

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[1] Consistent with the literature, we shall use the term 'willingness to pay' interchangeably with 'reservation price'. Alternative definitions will be discussed later in the chapter.

how much each of the target consumers is willing to pay for each of these services and the bundle, then it is straightforward to determine the optimal prices for the bundle and its components. As another example, suppose TiVo is planning to expand its digital video recorder (DVR) product line by offering a high-definition Series 3 DVR model. Suppose the market researcher knows how much each of the target consumers is willing to pay for this new product and each of the existing DVRs in TiVo's product line. Suppose that s/he also knows consumers' WTP for generic boxes from cable companies. Then s/he can determine which consumers will switch away from the cable companies to purchase the new DVR (the customer switching effect), the extent to which TiVo's new product will compete with the other DVRs in its own product line (the cannibalization effect), and how category sales are likely to expand (the market expansion effect) as a result of TiVo's new offering. (See Jedidi and Zhang, 2002 for other examples.)

The practical importance of knowing consumers' WTP is not limited to answering these managerial questions. Knowledge of WTP is also necessary for market researchers in implementing many other nonlinear and customized pricing policies such as bundling, quantity discounts, target promotions and one-to-one pricing (Shaffer and Zhang, 1995). Furthermore, such knowledge bridges the gap between economic theory and marketing practice. Specifically, it enables researchers to study a number of other issues related to competitive interactions, policy evaluations, welfare economics and brand value.

There is a vast literature in marketing and economics on the measurement of WTP and its use for demand estimation, pricing decisions and policy evaluations (see Lusk and Hudson, 2004 for a review). In marketing, we are witnessing a renewed interest in the measurement of WTP (Chung and Rao, 2003; Jedidi et al., 2003; Jedidi and Zhang, 2002; Wertenbroch and Skiera, 2002; Wang et al., 2007). This growing interest stems from three factors. First, pricing and transaction data (e.g. scanner panel data) are readily available to estimate consumer WTP. Second, the advent of e-commerce has made mass customization possible, thus motivating the need for more accurate measurement of WTP (Wang et al., 2007). Third, methodological advances in Bayesian statistics, finite mixture models and experimental economics allow one to obtain more accurate estimates of WTP at the individual or segment levels.

The goal of this chapter is to synthesize the WTP literature, focusing on the measurement of WTP and showing how this information can be used to improve decision-making. The chapter is organized as follows. Section 2 presents the various conceptual definitions of WTP. Section 3 reviews the advantages and disadvantages of alternative methods that have been proposed to measure WTP. Section 4 illustrates how WTP measures can be used for various pricing decisions. Section 5 summarizes the main points and discusses future research directions.

2. Conceptual definitions of WTP

Jedidi and Zhang (2002, p. 1352) define a consumer's reservation price as 'the price at which a consumer is *indifferent* between buying and not buying the product'. Formally, consider a consumer with income y, who is considering whether to buy one unit of product g priced at p or to keep her money. Let $U(g, y - p)$ be her utility from buying the product and $U(0, y)$ the utility from not buying it. Then, by definition, the consumer's reservation price $R(g)$ for product g is implicitly given by

$$U(g, y - R(g)) - U(0, y) \equiv 0 \tag{2.1}$$

This is the standard definition of consumer reservation price in economics, and captures a consumer's maximum WTP for product g, given consumption opportunities elsewhere and the budget constraint she faces. Jedidi and Zhang (2002) show that, under fairly general assumptions about the consumer's utility function, the reservation price $R(g)$ always exists, such that for any $p \leq R(g)$ the consumer is better off purchasing the product. They also show that if the utility function is quasi-linear,[2] then faced with a choice among G products ($g = 1, \ldots, G$), to make the optimal choice decision a utility-maximizing consumer will need to know only her reservation prices for the product offerings and the corresponding prices for these products.

These theoretical properties imply that knowing a consumer's reservation prices for the products in the category is sufficient to predict whether or not she will buy from the product category in question and which of these products she will choose. Specifically, the consumer will choose the product option that provides the maximum surplus ($R(g) - p$) subject to the constraint that $p \leq R(g)$. She will not buy from the category if the maximum surplus across products is negative (i.e. for each product in the category, the consumer's reservation price is always less than the price of that product). Thus knowledge of consumers' reservation prices allows us to distinguish and capture three demand effects that a change in price or the introduction of a new product will generate in a market: the customer switching effect, the cannibalization effect and the market expansion effect. Cannibalization (switching) results when consumers derive more surplus ($R(g) - p$) from a new product offering than from the company's (competitors') existing products. Market expansion results when non-category buyers now derive positive surplus from the new offering.

Other related definitions of WTP have been used in the literature. Kohli and Mahajan (1991) define reservation price as the price at which the consumer's utility (say for a new product) begins to exceed the utility of the most preferred item in the consumer's evoked set (i.e. the set of brands which the consumer considers for purchase). That is, the reservation price for a new product is the price at which the consumer is indifferent between buying the new product and retaining the old one. Hauser and Urban (1986) define reservation price as the minimum price at which a consumer will no longer purchase the product. Varian (1992) defines reservation price as the price at or below which a consumer will purchase one unit of the good. Ariely et al. (2003) argue for a more flexible definition of reservation price. Specifically, they suggest that there is a threshold price up to which a consumer definitely buys the product, another threshold above which the consumer simply walks away, and a range of intermediate prices between these two thresholds in which consumer response is ambiguous.

Implicit in all these definitions of reservation price is a link to the probability of purchase (0 percent in Urban and Hauser's definition, 50 percent in Jedidi and Zhang, and 100 percent in Varian's). In order to reconcile these alternative definitions, Wang et al. (2007) suggest that one should distinguish three reservation prices:

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[2] That is $U(g, y - p) = u(g) + \alpha(y - p)$ where $u(g)$ is the utility of product g and α is a scaling constant.

(a) *floor reservation price*, the maximum price at or below which a consumer will definitely buy one unit of the product (i.e. 100 percent purchase probability);
(b) *indifference reservation price*, the maximum price at which a consumer is indifferent between buying and not buying (i.e. 50 percent purchase probability); and
(c) *ceiling reservation price*, the minimum price at or above which a consumer will definitely not buy the product (i.e. 0 percent purchase probability).

3. Methods to measure WTP

Reservation prices can be estimated from either purchase data or survey/experimental data. The following methods based on survey/experimental data are commonly used: self-stated WTP, contingent valuation, conjoint analysis and experimental auctions. We consider several factors in evaluating the different measurement methods. The first factor concerns incentive compatibility. That is, how accurate is the method in providing an incentive to consumers to reveal their true WTP? The second factor concerns hypothetical bias. That is, how accurately can the method simulate the actual point-of-purchase context? Note that the issues of incentive compatibility and hypothetical bias are closely related to the conventional criteria of measurement reliability and internal and external validity in psychometric studies. The third factor pertains to the ability of the method to estimate reservation prices for new products with attributes that have not yet been made available in the market or have not varied sufficiently across products in the market to allow reliable estimation. A fourth factor relates to the ability of the method to measure WTP for multiple brands in a given category (e.g. different brands of toothpaste) or for multiple products across product categories (e.g. product bundles). This information is essential for estimating cross-price effects among new and competing products where the competing products could be products within a firm's product line, product items in a bundle, or competitive products.

3.1 Methods based on actual purchase data

These methods analyze scanner/household panel data, test-market data, or simulated test-market data. They provide two important advantages. Because the input data come from actual purchases, these methods are incentive compatible and do not suffer from hypothetical bias. Household panel data, for example, provide useful information about consumers' responses to the price changes of an existing brand and those of its competitors. Such information is useful for predicting the impact of a price change on category incidence, brand choice and quantity decisions (Jedidi et al., 1999). For new products, simulated test market methods such as ASSESSOR (Silk and Urban, 1978) and AC Nielsen BASES provide consumers with the opportunity to buy (real) new products at experimentally manipulated price points. In ASSESSOR, for example, participants are first shown advertisements for the new and existing products. Then they are given seed money that they can keep or use to buy any of the available products displayed in a simulated store. This experimental design provides data on how the demand for the new product varies across the posted prices.

Despite these advantages, however, methods based on actual purchase data have several weaknesses. The main shortcoming is that, because of cost, the firm must choose a limited number of price points for its own product. In addition, the firm can examine only a limited number of price combinations for market prices across competitors. For

example, suppose Procter & Gamble (P&G) is competing against three brands in a particular segment of the toothpaste market; in addition, P&G already has one brand of its own (say Crest) in that segment. Let's say that P&G wishes to test the impact of two price points for a new brand that it plans to introduce in this market segment. For simplicity, assume that each of the four incumbent brands (including P&G's own brand) can choose one of two price policies following the new product introduction. The first is to continue with the current price and the second is to reduce price. Then, it will be necessary for P&G to run 32 ($=2^5$) separate experiments to examine all the feasible competitive scenarios before choosing a pricing plan for the new product.

In addition, as Wertenbroch and Skiera (2002) note, data from purchase experiments provide only limited information about WTP. To illustrate, suppose P&G conducts an ASSESSOR study for a new product. Let's say that, for the posted set of prices for the new product and its competitors, 30 percent of the respondents purchase the new product. Then the only inferences that P&G can make are the following. Given the posted set of market prices, 30 percent of the respondents obtain maximum (positive) surplus by purchasing the new product. The remaining 70 percent of the respondents obtain maximum surpluses by buying another brand or not purchasing a brand in the product category. Note that this information is extremely limited. Specifically, since the experiment does not provide estimates of WTP *per se*, P&G cannot estimate new product demand for any other price for the new product or its competitors. Hence P&G cannot use the purchase data to determine the optimal price for the new product or the optimal product line policy.

3.2 Self-stated WTP

This method directly asks a consumer how much she is willing to pay for the product. Consequently, this is perhaps the easiest method to implement. However, for a number of reasons, this method is likely to lead to inaccurate results. Perhaps the most serious problem is that the consumer is not required to purchase the product. Hence the methodology is not incentive compatible. A related problem is that consumers are likely to overstate their WTP for well-known or prestigious brands or for products they are keenly interested in. They are also likely to understate their WTP for less well-known brands or if they anticipate being charged a higher price for the product in the future. Finally, even if consumers are able to correctly state their WTP on average, this method will overstate the degree of heterogeneity in WTP in the population.[3] Hence the firm will make suboptimal pricing decisions using self-stated WTP data.

An interesting managerial question is whether self-stated WTP are similar to the estimates obtained by using other methods. Jedidi and Zhang (2002) examined the correlation between self-stated WTP for different brands of notebook computers and WTP that were estimated using a conjoint experiment. (We shall discuss the conjoint methodology in subsection 3.4.) The results for two brands showed that the correlations were low (0.43 and 0.28 respectively). The correlation coefficient for the third brand was not statistically significant. Furthermore, the self-stated WTP led to excessively high estimates of demand

[3] The variance of the observed WTP is always greater than or equal to the variance of the true WTP.

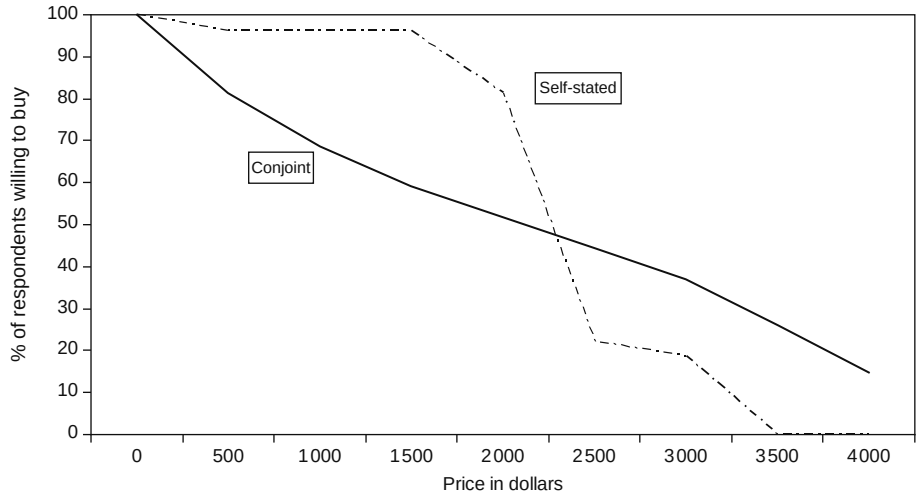

Figure 2.1 Conjoint versus self-stated demand estimates

at low prices and significantly understated the demand at high prices. Figure 2.1 shows the demand functions obtained from both methods for a Dell notebook computer with 266 mHz in speed, 64 MB in memory, and 4 GB in hard drive.[4] These results strongly support the observation in the previous paragraph that the firm should not use self-stated WTP to make pricing decisions.

3.3 Contingent valuation methods

Contingent valuation (CV) is a popular WTP measurement method in agricultural economics and in determining the economic impact of changes in social policy. This method uses dichotomous choice questions to arrive at an estimate of WTP for each respondent in the experiment. In a marketing CV study, the researcher presents consumers with a new product, including its price, and asks them whether they would buy the new product at the listed price (Cameron and James, 1987). Thus a yes response indicates that the consumer is willing to pay *at least* the listed price for the new product. When these yes responses are aggregated across consumers, one obtains a demand curve that shows how the proportion of yes responses varies across the experimentally manipulated price levels.

Estimating WTP from CV data is straightforward using a binary choice model such as logit or probit (Cameron and James, 1987). In such a choice model, the decision of whether to buy or not is modeled through a latent utility function that depends on product characteristics and consumer background variables. Let p_i be the price of the new product given to consumer i. Let I_i be a variable that indicates whether consumer i decided to buy $(I_i = 1)$ or not $(I_i = 0)$. Let $U_i = \mathbf{x}_i'\hat{\mathbf{a}} + \varepsilon_i$ be the latent utility of the

[4] The percentage willing to buy is the percentage of respondents whose WTP is higher than the observed price.

product concept, where $\mathbf{x}_i$ is a vector of explanatory variables that includes product characteristics (excluding price) and individual-specific consumer background variables, $\hat{\mathbf{a}}$ is a vector of associated parameters, and $\epsilon_i$is an error term. Then the binary choice model is given by

$$I_i = \begin{cases} 1 & \text{if } U_i - p_i > 0 \\ 0 & \text{otherwise} \end{cases} \tag{2.2}$$

Since the price coefficient is set to -1 in equation (2.2), $U_i - p_i$ is a measure of consumer surplus and U_i is therefore a direct measure of WTP. In this model, the $\hat{\mathbf{a}}$ parameters capture the marginal WTP for each of the explanatory variables included in the model.

The main advantage of the CV method is that it is easy to implement. However, the method has several weaknesses. The CV method allows the researcher to observe only whether an individual's WTP is higher or lower than the listed price. Hence it may be necessary to use large samples or multiple replications per respondent to obtain accurate results.

One modification of the basic CV method is to use a sequential approach to obtain more precise information about WTP. In the first step, the researcher asks a consumer to respond to a dichotomous (yes–no) question. Depending on the response, the researcher asks the consumer an additional dichotomous follow-up question. Specifically, if the initial response is no (yes), then the consumer is asked whether she would buy the new product at a lower (higher) price. This data collection procedure is called a double-bounded dichotomous choice question (Lusk and Hudson, 2004). Although this sequential method can provide more information on the true WTP, it is subject to starting-point biases (i.e. the consumer's response to the follow-up question depends on the initial price offered; see Shogren and Herriges, 1996; Hanemann et al., 1991).

Research evaluating the CV method suggests that it is not incentive-compatible and is also subject to hypothetical bias. For example, Bishop and Heberlein (1986) found that WTP in the hypothetical condition were significantly overstated compared to those in the actual cash condition. Finally, in a meta-analysis of 14 valuation studies using the CV method, List and Gallet (2001) found that, on average, subjects overstated their WTP by a factor of 2.65 in hypothetical settings.[5] However, the overstatement factor was much lower for private goods (=1.65) compared to public goods (=5). This finding is intuitive since most subjects are more confident in valuing products they commonly purchase than in valuing products that they may be unfamiliar with (e.g. public goods).

Most applications of the CV method vary list prices across consumers while holding the product concept description constant. In principle, the basic CV method can be modified so that data on WTP for different combinations of price and product concepts (which are typically multidimensional) are obtained. However, as discussed earlier, the experimental design becomes very expensive and unwieldy. Thus the CV method is not feasible for predicting WTP when the firm is considering several alternative product designs – as is generally the case. Finally, and most importantly from a strategic viewpoint, the CV

[5] The overstatement factor is calculated as the ratio of the mean hypothetical WTP to the mean actual WTP. The actual WTP are obtained from experiments with real economic commitments.

method considers only one product. Thus the firm cannot determine the separate effects of the new product (including product design and price) on brand switching, cannibalization and market expansion. Without this disaggregate information across different products and segments in the market, the firm cannot choose its optimal product-line policy. In particular, the firm cannot determine the net effect of its new product policy on product-line sales and profits after allowing for competitive reaction.

3.4 Conjoint analysis

Conjoint analysis is a popular WTP measurement method in marketing, transportation and environmental economics. Two common types of conjoint studies are the rating-based and the choice-based conjoint (CBC) methods. In a rating-based conjoint study, researchers present consumers with a number of hypothetical product profiles (concepts) and ask them to rate *each* of these profiles on a preference scale.[6] Sometimes researchers ask consumers to proceed sequentially (Jedidi et al., 1996). In the first step, consumers decide whether or not they will consider a particular product profile for purchase. In the second step, consumers rate only those profiles that they are willing to consider (i.e. profiles in the consideration set). In contrast, in a CBC study, researchers present consumers with *several sets* of hypothetical product profiles and ask them to choose at most one from each set.

To illustrate the conjoint methodology, consider the following example. Suppose a yogurt manufacturer is planning to introduce a new type of yogurt into the marketplace. The first, and perhaps most important, step is to determine the salient attributes. (See Lee and Bradlow, 2007 for an interesting approach for deriving attributes and levels using online customer reviews.) Let's say that the firm has determined that the relevant attributes are the quantity of yogurt in a container, whether or not the yogurt is fat-free, the flavor of the yogurt, the brand name (e.g. Dannon, Breyers, Yoplait) and the price. Then a product profile (or equivalently product concept) consists of a particular combination of attributes including price. For example, one product profile is the following: a 6-ounce, fat-free, vanilla-flavored yogurt that is made by Yoplait and priced at $1. In a rating-based conjoint experiment, the researcher first determines the set of profiles to be evaluated. Then consumers provide preference rating scores for all profiles that they are asked to evaluate. If a sequential approach is used, consumers first sort profiles and then provide ratings scores for those profiles that they consider acceptable.

In a CBC experiment, the researcher first determines the sets of profiles that consumers will be asked to evaluate. For example, one set of profiles might contain the following options: a 6-ounce, fat-free, vanilla-flavored yogurt made by Yoplait and sold at a price of $1 (Alternative 1); a 10-ounce, full-fat, chocolate-flavored yogurt made by Dannon and sold at a price of $1.50 (Alternative 2); and the no-purchase option (Alternative 3). Then the consumer's task is to choose one of these three alternatives. Similarly, the consumer is offered different sets of profiles and asked to pick the best alternative for each profile in that set. A critical feature of the experimental design is that the no-purchase option must be included in each set of profiles that the consumer is asked to evaluate.

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[6] Our discussion of conjoint analysis is based on the full-profile method. That is, the consumer is given information about all product attributes simultaneously.

This no-purchase alternative must be included so that we obtain unambiguous monetary values for the WTP. (See appendix in Jedidi et al., 2003.)

Whether the CBC or rating-based conjoint method is used, the product profiles or choice sets included in a study must be carefully chosen using an efficient experimental design (Louviere and Woodworth, 1983). Regardless of the method used for data collection, the end result of a conjoint study is an estimated, individual-level utility function that describes how the consumer trades off different attributes.

The key question is the following: how can one use the conjoint results to infer consumers' WTP for different product designs? Using basic principles from the economic theory of choice, Jedidi and Zhang (2002) show how to derive consumers' reservation prices for a product from the individual-level estimates of conjoint coefficients. Let $\mathbf{x}_j$ be a vector that describes the attribute levels of product profile j and $\hat{\mathbf{a}}_i$ be the vector of the associated parameters (part-worth coefficients) for consumer i.[7] Let p_j be the price of profile j and y_i be consumer i's income.[8] Then the (quasi-linear) utility consumer i derives from purchasing one unit of product j is $U_{ij} = \mathbf{x}_i'\hat{\mathbf{a}}_i + \alpha_i(y_i - p_j)$, where α_i denotes the effect of an increase in income (the income effect) or of a decrease in price (the price effect). For any set of profiles in a choice set, if the consumer chooses the no-purchase option (i.e. she decides to keep the money), then her utility is simply $U_{ij} = \alpha_i y_i$. Using the definition in equation (2.1), Jedidi and Zhang (2002) show that for this utility specification, a consumer's reservation price for product profile j is defined by

$$R(j) = \frac{\mathbf{x}_j'\hat{\mathbf{a}}_i}{\alpha_i} \tag{2.3}$$

To illustrate the relationships among the conjoint part-worth coefficients and reservation prices, suppose we conduct a CBC study and obtain the following individual-level utility function for consumer i for product j:

$$U_{ij} = 0.2 + 0.15\ \text{Dannon} + 0.05\ \text{Yoplait} + 0.15\ \text{Banana} - 0.10\ \text{Strawberry} - 0.5\ \text{Price}$$

where Breyers and Vanilla, respectively, are the base-level brand and flavor and price is measured in dollars.[9] Thus, for this consumer, the reservation price for the Yoplait brand that has a Banana flavor is \$0.80 = (0.2 + 0.05 + 0.15)/0.5. In addition, a \$1 change in price reflects a utility difference of 0.5. Therefore every change of one unit in utility is equal to \$2.00 in value (=1/0.5). This ratio is what Jedidi and Zhang (2002) define as the 'exchange rate' between utility and money for the consumer. In the example, the exchange rate implies that, for any product flavor, consumer i is willing to pay up to an additional \$0.10 to acquire a Yoplait relative to a Breyers yogurt (=0.05 × \$2.00).

Conjoint analysis, in its CBC form, can be viewed as an extension of the conventional

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[7] For simplicity, we assume that there are no interactions among the product attributes. The analysis can easily be extended to allow for such interactions in conjoint models.

[8] The consumer's income need not be observable, but one has to postulate its existence to develop an economic model.

[9] In any conjoint experiment, it is necessary to choose a base level for each product attribute (e.g. brand and flavor in the yogurt example). The choice of base levels does not affect the results.

contingent valuation (CV) method in two ways. First, in CV, the product to be evaluated is typically fixed across respondents. In contrast, the product profiles in conjoint experiments are experimentally manipulated, hence resulting in a within-subject design. Second, conjoint analysis provides additional information about reservation prices. Thus CV provides information only about whether or not the new product is chosen. In contrast, CBC provides detailed information about the case where the new product is not chosen. Specifically, one can distinguish whether the consumer who does not purchase the new product chooses another product (brand) alternative or the non-purchase option.

Because of this additional information, CBC provides several important advantages over CV. The choice task in CBC is more realistic than in CV and closely mimics the consumer's shopping experience. Hence CBC minimizes hypothetical bias. Interestingly, previous research findings show that the responses to CBC questions are generally similar to those from experiments based on revealed preference (e.g. Carlsson and Martinsson, 2001). In the few cases where the differences in the results from the two methodologies are statistically significant, the differences are small (Lusk and Schroeder, 2004). An additional advantage of CBC is that, when the experiment manipulates several attributes simultaneously, consumers are more likely to consider other attributes than price in making the choice decision. Consequently, the task becomes more incentive-compatible. From a managerial viewpoint, perhaps the most important advantage of CBC is the following. In contrast to CV, CBC provides disaggregate information that allows the firm to distinguish how much of the demand for the new product comes from brand switching, cannibalization and market expansion. Consequently, the firm can choose the optimal product-line policy after allowing for the likely effects of competitive reaction following the new product introduction.

The estimation of conjoint models is straightforward regardless of whether we have choice or preference rating data.[10] With rating-based data, one can use regression to estimate the conjoint model. In the special case where consumers provide rating scores only for profiles that are in their consideration sets, one can use a censored-regression model such as tobit to estimate the conjoint model (see Jedidi et al., 1996). With CBC data, the individual-level conjoint model is typically estimated using a hierarchical Bayesian, multinomial logit (MNL) or probit model (Jedidi et al., 2003; Allenby and Rossi, 1999). The primary advantage of the MNL model is computational simplicity. However, the MNL method makes the restrictive assumption of independence of irrelevant alternatives (i.e. the ratio of the choice probabilities of two alternatives is constant regardless of what other alternatives are in a choice set). If researchers are interested in obtaining segment-level estimates of WTP, they can use finite-mixture versions of these models.

Although the methods described above will work in many cases, there are a number of potential pitfalls that one can encounter when estimating WTP. The quasi-linear utility model that we have discussed above is strictly linear in price. While this specification is consistent with utility theory, a consumer's reaction to price changes need not be linear,

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[10] Software for estimating conjoint models is readily available (e.g. SAS, SPSS and Sawtooth Software). Note that one does not need to observe consumer's income to infer WTP. Because $\alpha_i y_i$ is specific to consumer i, it cancels out in a choice model and gets absorbed in the intercept in a regression model.

especially when the price differences across alternatives are large. In such cases, Jedidi and Zhang (2002, p. 1354) suggest using the exchange rate that corresponds to the price range that the firm is considering for the new product. Another issue arises if the price coefficient α_i is unconstrained and the estimated coefficient has the wrong sign for some consumers. Thus, suppose some consumers use price as a signal for quality. In such a case, price has two opposing effects. On the one hand, it acts as a constraint since the higher the price paid, the worse off the consumer is. On the other hand, since price is a signal of quality, the higher the price, the higher the utility. Because of these competing effects, it is possible that the estimated WTP measures for these consumers will be negative; see equation (2.3). Another potential difficulty can arise if the price coefficient for a particular respondent is extremely small (close to zero). This can happen if consumers are insensitive to price changes or the data are noisy. In this case, the exchange rate (and hence WTP) may be large and can even approach infinity. One way to address these difficulties is to constrain the price coefficient so that lower prices always have higher utilities. Another frequently used approach is to constrain the price coefficient to be the same across consumers in the sample (e.g. Goett et al., 2000). A third approach is to constrain the price coefficient to 1 (see equation 2.2). In a choice model, this means that consumers maximize surplus instead of utility. The latter two methods are equivalent if the utility function is quasi-linear (see Jedidi and Zhang, 2002). In most practical applications, all three approaches lead to price coefficients that are non-zero and have the proper signs.

3.5 Experimental auctions

Auction-based methods are beginning to gain popularity in marketing because they measure real and not self-stated choices. We discuss below the following auction mechanisms: the Dutch auction; the first-price, sealed-bid auction; the English auction; the *n*th-price, sealed-bid auction (Vickrey, 1961); the BDM method (Becker et al., 1964); and the reverse auction (see Spann et al., 2004).

In a Dutch auction, the opening price is high and is progressively lowered until one bidder is willing to purchase the item being auctioned. Thus the only information that is available to the firm is that the winner's WTP is at least as high as the price at which the item was sold; in addition, the WTP of all other bidders are lower than this price. Given this auction mechanism, a bidder's bidding strategy will depend on her beliefs about others' bidding strategies; in addition, her strategy will depend on her risk attitude. Consequently, all bidders have an incentive to underbid. In particular, the person with the highest reservation price may not always submit the highest bid. Note that, from a managerial viewpoint, the information from a Dutch auction is extremely limited. All that the firm knows is the (potentially understated) maximum price at which it can sell one unit of its product. Thus, suppose there are three bidders (A, B and C) and A wins the auction at a bid price of $200. Then the only quantitative demand information available to the firm is the following. If it sells one unit, it can obtain a minimum price of $200. However, since bidders have an incentive to underbid, this price may be too low. Furthermore, the results provide no information about market demand if the firm plans to sell more than one unit in the marketplace.

In the first-price, sealed-bid auction, each bidder submits one bid. This information is submitted to the auctioneer and is not provided to the other bidders. The highest bidder wins the auction and pays her bid price. Note that, as in the Dutch auction, each bidder

has an incentive to bid less than her reservation price. However, in contrast to the Dutch auction, the firm obtains more detailed information about the demand structure for its product. Thus, suppose there are three bidders (A, B and C) as before. Let's say that the sealed bids are as follows: A bids $100, B bids $160, and C bids $250. Then the firm knows the following information about demand. If it wants to sell one unit, the minimum price that it can charge is $250 per unit. If it wants to sell two units, the minimum price that it can charge is $160 per unit. If it wants to sell three units, the minimum price that it can charge is $100. Note that, in contrast to the Dutch auction, the firm obtains market demand information for different volumes. However, since all bidders have an incentive to underbid, the firm is likely to choose a suboptimal price.

In an English auction, participants offer ascending bids for a product until only one participant is left in the auction. This bidder wins the auction and must purchase the auctioned product at the last offered bid price. Note that, in contrast to the first-price, sealed-bid auction, the English auction is an 'open' auction. Specifically, all bidders know each other's bids. This experimental design is useful in situations where it is important to incorporate market information into participants' valuations (e.g. potential buyers are likely to communicate with each other). However, this method can be a limitation if consumers make independent valuations in real life (Lusk, 2003). In addition, because the bids are 'open', the last bid tends to be only marginally higher than the second-highest bidder's last bid.

Note that, in contrast to the Dutch auction and the first-price, sealed-bid auction, bidders in an English auction have an incentive to reveal their true reservation prices.[11] That is, a bidder will drop out of the auction only when the last bid exceeds her reservation price. From a managerial viewpoint, the firm obtains much more detailed information about the market demand for its product. For simplicity, assume that there are three bidders (A, B and C). Suppose A drops out when the price is $10, B drops out when the price is increased to $15, and C purchases the product at a price of $16. These results imply the following market demand structure. If the firm wants to sell three units, the maximum price it can charge is $10 per unit. If the firm wants to sell two units, the maximum price it can charge is $15 per unit. Note that these results do not imply that the maximum price that the firm can charge for one unit is $16. Specifically, bidder C needs only to bid marginally more ($16) than bidder B, who drops out when the price is raised to $15. The only inference is that bidder C's minimum reservation price is $16. From a practical viewpoint, it is likely that, in most cases, the firm will sell more than one unit. Hence the firm can use the results of an English auction to determine what price to charge for its product.[12]

In an nth-price, sealed-bid auction (Vickrey, 1961), each bidder submits one sealed bid to the seller. None of the other bidders is given this information. Once bids have been made, the $(n - 1)$ highest bidders purchase one unit each of the product and pay an amount equal to the nth-highest bid. Perhaps the most commonly used nth-price auction

[11] This conclusion of incentive compatibility holds if the auction is not conducted repeatedly with the same group of bidders and bidders cannot purchase more than one unit. If either of these assumptions does not hold, bidders may behave strategically and systematically choose bid prices that are lower than their WTP.

[12] This analysis assumes that consumers will not purchase multiple items of the product.

is the second-price ($n = 2$) auction in which the highest bidder purchases the product at the second-highest bid amount. Similarly, suppose the firm uses the fourth-price auction (n = 4). Then the three highest bidders will purchase one unit each at the price bid by the fourth-highest bidder. Because of the sealed-bid mechanism, the participants in this auction learn only the market price and whether or not they are buyers in the auction.

As Vickrey (1961) shows, the second-price, sealed-bid auction is isomorphic to the English auction. This is because the final price paid in both auctions is determined by the bid of the second-highest bidder. Furthermore, both the English and *n*th-price auction mechanisms are incentive compatible. Hence, in principle, the firm can use either the English auction or the *n*th-price, sealed-bid Vickrey auction to determine the optimal price when it sells more than one unit.[13]

Despite the theoretical advantages of the Vickrey auction methodology, the method has several drawbacks as a marketing research tool for measuring WTP (Wertenbroch and Skiera, 2002). The first limitation concerns the operational difficulties in implementing the method in market research. The second stems from the fact that the bidding process in the auction does not mimic the consumer purchase process (Hoffman et al., 1993). The third limitation stems from the limited stock of products being auctioned. This is not only unrealistic for many products in retail settings; it also encourages participants to bid more than the true worth of the product to ensure that they are placing the winning bid (e.g. Kagel, 1995). Finally, empirical findings suggest that low-valuation participants become quickly disengaged in these auctions when they are conducted in multiple rounds (Lusk, 2003). Thus subjects quickly learn that they will not win the auction and drop out of the auction by bidding zero.

To address some of these limitations, Wertenbroch and Skiera (2002) propose the use of the incentive-compatible, BDM (Becker et al., 1964) method for eliciting WTP. The BDM method is as follows. Each participant submits a sealed bid for one unit of the product. The auctioneer then randomly draws a 'market' price. If the participant's bid exceeds this value, the participant is required to purchase one unit of the product at the market price. If the bid is lower than the market price, the bidder does not purchase the product. Note that, although the BDM method is structurally similar to the standard auction method, there is a fundamental difference. The BDM procedure is not an auction because participants do not bid against one another (Lusk, 2003).

One important practical advantage of the BDM procedure over standard auctions is that it does not require the presence of a group of consumers in a lab for bidding. This feature makes it possible to more accurately mimic the purchase decision process by eliciting WTP at the point-of-purchase (Wertenbroch and Skiera, 2002; Lusk et al., 2001). In addition, because the supply of the product is not limited, every consumer can buy the product as long as his or her WTP is greater than the randomly drawn price. This aspect makes low-valuation participants more likely to be engaged in the experiment. One drawback of the BDM method is the absence of an active market such that participants can incorporate market feedback. Empirical findings, however, suggest that the BDM method and the English auction generate similar results (Lusk et al., 2002; Rutström, 1998).

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[13] This result holds provided the auction is not repeated with the same group of bidders. For this scenario, bidders may behave strategically and not reveal their true reservation prices.

Another type of auction mechanism is the reverse auction – a method used by such Internet firms as Priceline.com. The reverse auction method works as follows. The seller specifies a time period (e.g. the next seven days from now) during which it will accept bids to purchase a product. During this period, each bidder is allowed to submit one bid for the product.[14] Only the seller has access to bids. The outcome of the auction is as follows. The seller has a secret threshold price below which she will not sell the product. If a consumer bids more than the threshold price, the consumer must purchase one unit of the product at his or her bid price. If the consumer bids less than the seller's threshold price, the seller will not sell the product to the consumer. Note that the reverse auction is similar to the BDM method in that bidders do not compete with each other. However, there is an important difference. In a BDM auction, the buyer pays the randomly drawn market price. In a reverse auction, each buyer pays her bid price if offered the option to purchase.

To illustrate how the reverse auction works, suppose a hotel wishes to sell excess capacity (e.g. three room nights on a given Saturday one month after the auction is conducted). Since the marginal cost of a room night is low, let's say that the hotel's secret threshold price per room night is $20. Suppose the firm conducts the reverse auction over a seven-day period and the room-night bids in descending order are as follows: $60 (Consumer A); $50 (Consumer B); $40 (Consumer C); $30 (Consumer D); and a number of bids less than $30. Then the hotel will choose the following room-night pricing plan. It will charge A a price of $60, B a price of $50, and C a price of $40 for the Saturday night stay. Note that, in contrast to standard auctions, consumers pay different prices for the same product. In our example, the reverse auction method allows the hotel to ration out the limited supply of room nights by using a price discrimination (price-skimming) strategy.

From a managerial viewpoint, reverse auctions are a mixed blessing. On one hand, they allow the firm to extract consumer surplus from the market by charging differential prices. Furthermore, they are a convenient, low-cost method for the firm to sell excess capacity without disrupting the price structure in traditional distribution channels. On the other hand, reverse auctions are not incentive compatible. Specifically, customers will bid less than their true WTP in order to obtain a surplus from the transaction. This lack of incentive compatibility reduces the ability of the firm to extract consumer surplus from the market. To address this problem, some researchers have suggested the following modification: allow bidders to submit multiple bids but require each bidder to pay a bidding fee for each bid submitted (Spann et al., 2004).

3.6 Comparison of WTP methods

Experimental auctions (EAs) can provide several advantages over stated preference methods. Many auction methods are incentive compatible. That is, bidders have an incentive to reveal their true WTP. In contrast to stated preference methods, EAs are conducted in a real context that involves real products and real money. In addition, by putting subjects in an active marketing environment, some EAs allow one to estimate WTP after allowing for a market environment with feedback among buyers. Depending on the purchase context, this feature may be important. WTP from EAs are empirically

[14] Some reverse auctions allow bidders to make multiple bids. See, e.g., Spann et al. (2004).

observed. Hence one can obtain individual-level estimates of WTP without making parametric assumptions (e.g. normality) about the distribution of WTP in the population.

However, in spite of these advantages, the EA methodology is not a panacea for measuring WTP. The elicitation process does not mimic the actual purchase process that a consumer goes through, including search for information. The EA method focuses on one product/product design only. Hence one cannot measure the cannibalization, substitution and market-expansion effects of a new product entry. Nor can one determine how consumers trade off attributes. Consequently, the EA method can be used only at a late stage of the product development process when the firm has finalized the product design and the remaining issue is to choose the price conditional on this product design. Since participants in an EA study are expected to pay for the products they purchase, the EA method cannot be used to determine the reservation prices for durables (Wertenbroch and Skiera, 2002). The EA method assumes that reservation prices are deterministic. This may not be the case, especially for new products or products with which the consumer is unfamiliar. It may be difficult to generalize the WTP estimates from an EA study to a national level because it is infeasible to recruit a sufficiently large and representative sample. Subjects must be recruited and paid participatory fees to attend laboratory sessions. This potentially introduces bias into the resulting bids (Rutström, 1998). Depending on the EA method used, bidder values may become affiliated (i.e. a relatively high bid by one auctioneer induces high bids from others). This degrades the incentive compatibility of an auction (Lusk, 2003). In addition, it is not uncommon to observe a large frequency of zero-bidding, potentially because of lack of participant interest (Lusk, 2003). Hence the firm obtains incomplete information about the demand structure in the market.

Empirical studies comparing WTP measures across methods are limited. In three studies, Wertenbroch and Skiera (2002) find that WTP estimates from BDM are lower than those obtained from open-ended and double-bounded contingent valuation methods. Similarly, Balistreri et al. (2001) find that bids from an English auction are significantly lower than those obtained from open-ended and dichotomous CV methods. Lusk and Schroeder (2006) find that the WTP estimates from various auction mechanisms are lower than those from CBC. These findings may be due to the incentive compatibility of the auction methods and to the hypothetical bias inherent in the CV and conjoint analysis methods. In contrast, Frykblom and Shogren (2000) found that they could not reject the null hypothesis that WTP estimates obtained from a non-hypothetical (dichotomous) CV method are equal to those obtained from a second-price auction.

3.7 Emerging approaches

A new stream of research is emerging in marketing that combines the advantages of the stated preference methods with the incentive compatibility of the BDM method. Ding et al. (2005) extended the self-stated WTP and CBC methods using incentive structures that require participants to 'live with' the consequences of their decisions. Using Chinese dinner specials as the context, the authors conducted a field experiment in a Chinese restaurant during dinner time. For the self-stated condition, consumers were presented with a menu of 12 Chinese dinner specials (with no price information) and were asked to state their WTP for each meal in the menu. Consumers were told upfront that a random procedure would be used to select a meal from the menu and that they would receive this meal if their WTP exceeded a randomly drawn price. For the CBC condition, the authors

presented consumers with 12 choice sets of three Chinese meals each (with price information) and asked them to choose at most one meal from each choice set. Consumers in this condition were told upfront that a random lottery would be used to draw one choice set and that they would receive the meal that they selected from that choice set. (The consumer would receive no meal if she selected none of the meals in the choice set.) For both experimental conditions, the price of the meal (random price for the self-stated method and menu price for CBC) would be deducted from their compensation for participating in the study. The out-of-sample predictions show that the incentive-aligned conjoint method outperformed both the standard CBC and incentive-aligned, self-stated WTP methods.

More recently, Park et al. (2007) proposed a sequential, incentive-compatible, conjoint procedure for eliciting consumer WTP for attribute upgrades. This method first endows a consumer with a basic product profile and a budget for upgrades. In the next step, the consumer is given the option of upgrading, one attribute at a time, to a preferred product configuration. During this process, the consumer is required to state her WTP for each potential upgrade she is interested in. In addition, the BDM procedure is used to ensure that the incentive-compatibility condition is met. That is, the consumer receives the upgrade only if her self-stated WTP for the upgrade exceeds a randomly drawn price for that upgrade. When no further upgrade is desired by the consumer or the consumer's upgrade budget is exhausted, the consumer receives the final upgraded product. The authors tested their model using data collected from an experiment on the Web to measure consumers' WTP for upgrades to digital cameras. The out-of-sample validation analysis shows that the new method predicted choice better than the benchmark (self-explicated) conjoint approach.

4. Using WTP for pricing decisions

So far, we have focused on empirical methods for measuring WTP. In this section we discuss how managers can use WTP measures to choose pricing policies. We discuss three application areas: bundling, quantity discounts and product line pricing decisions.

4.1 Bundling

Consider a cable company, say Comcast, which sells two services: a basic digital cable service and high-speed online service. Suppose Comcast has conducted market research and obtained the WTP measures shown in Table 2.1 for its bundled and unbundled services for four segments in the market. (We shall discuss empirical methods to estimate the WTP for bundles later in this section.)

Table 2.1 WTP for individual services and bundle in dollars

Segment	Average WTP for		
	Cable service	High speed online service	Bundle
1	50	10	55
2	50	43	90
3	45	45	90
4	15	48	55

Suppose all segments are of equal size (1 million customers each) and the marginal cost of providing each service is zero. Then a consumer will only consider buying a particular service or bundle if the price charged is less than her WTP for that service or bundle. In addition, she will choose the alternative that maximizes her surplus (= WTP for any service or bundle – price of that service or bundle). If the maximum surplus is negative, the consumer will not purchase any of the services or the bundle.

Given this information about WTP and costs, Comcast can choose from among three pricing strategies: a uniform pricing strategy, a pure bundling strategy, or a mixed bundling pricing strategy. If Comcast uses uniform pricing, it will sell each service separately at a fixed price per unit. If Comcast uses pure bundling, it will only sell the two services as a package for a fixed price per package. If Comcast uses mixed bundling, it will sell the services separately and as a package.

Suppose Comcast uses a uniform pricing strategy. Then, using the WTP information in Table 2.1, we see that the optimal price for the cable service is $45. If this price is chosen, Comcast's profit from the cable service will be $135 million. Similarly, the optimal price for high-speed online service is $43 and the profit from this service is $129 million. Hence Comcast's product line profit if it uses a uniform pricing strategy is $264 million (= profit from cable service + profit from high-speed online service).

Suppose Comcast uses a pure bundling policy. Then the optimal price for the bundle is $55 and the product line profit is $220 million. Finally, if Comcast uses a mixed bundling strategy, the optimal policy is to charge $90 for the bundle, $50 for the cable service alone, and $48 for the high-speed online service. Hence Comcast's product line profit will be $278 million (= 180 + 50 + 48). Consequently, the optimal product line policy is to use a mixed bundling strategy.

The previous discussion assumed that the manager knows the WTP for the individual products and the bundles. So far, we have discussed only how to estimate WTP for individual products. How can one estimate the WTP for product bundles? One way is to use self-stated WTP. However, as discussed, these are likely to be inaccurate, especially for new products or for products with which the consumer is unfamiliar. Another approach is to use the individual-level, choice-based method developed by Jedidi et al. (2003) or a modified version that allows segment-level estimation. This method is philosophically similar to the choice-based methods discussed earlier. That is, consumers seek to maximize their surpluses. As shown by Jedidi et al., their choice-based method provides more accurate estimates of reservation prices than the self-stated methodology. In practical applications, the data will be more complex than in the example above. For example, there will be many more segments, products and bundles. In such cases, the choice of the optimal bundling policy is complicated. One approach is to use an optimization algorithm (e.g. Hanson and Martin, 1990) to analyze the WTP results and cost data for the products and bundles in question.

4.2 Quantity discounts/nonlinear pricing

Suppose the Marriott Hotel seeks to determine how to price different packages for its standard rooms. Suppose the average WTP measures for stays of different durations in the hotel for three leisure segments are as shown in Table 2.2. Furthermore, assume that Marriott has sufficient room capacity to meet all demand.

Note that for any given consumer segment, the WTP is the highest for the first night

Table 2.2 WTP in dollars for a hotel night for different stay durations

Night	Segment 1	Segment 2	Segment 3
First	90	100	120
Second	60	75	100
Third	35	55	80
Fourth	20	40	60
Fifth	11	15	35

Table 2.3 Pricing of hotel night stays

Night	Optimal price for *n*th night ($)	Number of night stays	Sales revenues ($)
First	90	3000	270,000
Second	60	3000	180,000
Third	55	2000	110,000
Fourth	40	2000	80,000
Fifth	35	1000	35,000
Total		11,000	$675,000

and decreases for every successive night. Suppose the three segments are of equal size (1000 customers) and that the hotel's marginal cost per room is approximately zero. (This is a reasonable assumption since most costs for maintaining hotel rooms are fixed.) Hence any pricing policy that maximizes sales revenue also maximizes profits.

One option for Marriott is to set a uniform price per night, regardless of the duration of stay. Following the same procedure as in the bundling case, we find that the sales-revenue maximizing price is $55 per night. If Marriott uses this uniform pricing plan, it will sell 9000 hotel night stays and obtain a revenue (gross profit) of $495,000. An alternative pricing strategy is to use a quantity discount pricing plan based on the 'price-point' method (see Dolan and Simon, 1996, p. 173). Using this approach, Marriott will proceed sequentially and set the revenue-maximizing price for each successive night stay. Table 2.3 presents the optimal pricing results using the price-point method.

Thus, for the first night the optimal price is $90. This pricing policy leads to 3000 night stays and a revenue of $270,000. Conditional on this pricing policy, the optimal price for the second night is $60, yielding 3000 night stays and a revenue of $180,000. Conditional on the prices for the first two nights, the optimal price for the third night is $55. Note that Segment 1 will not stay for a third night because its WTP for the third night ($35) is lower than the price for the third night ($55). Hence the hotel will sell 2000 night stays and obtain a revenue of $110,000. Similarly, we can determine the number of night stays and the corresponding revenues for the fourth and fifth nights (see Table 2.3). Given this price-point strategy, Marriott will sell 11,000 night stays and make a gross profit of $675,000. Note that, when Marriott uses a quantity discount pricing plan, it sells more hotel room nights and obtains a higher profit than if it uses uniform pricing. Specifically, the number of hotel night stays increases from 9000 to 11,000 (a 22 percent increase)

Table 2.4 WTP for different models of notebook computers by Dell and Hewlett-Packard ($)

Segment	WTP for			
	DELL	HP_C	HP_L	HP_H
1	1700	1200	500	1300
2	1600	1100	600	1650
3	1200	1500	700	1700
4	1000	1400	800	1500
5	900	900	900	900

Note: DELL = The notebook model made by Dell; HP_C = The initial notebook made by HP; HP_L = Lower-quality notebook to be made by HP; HP_H = Higher-quality notebook to be made by HP.

and gross profits increase even more sharply from $495,000 to $675,000 (a 36 percent increase).

As discussed, WTP information of the type presented in Table 2.2 can be collected in a number of different ways. For example, one can use conjoint or choice-based experiments where the quantity of product (e.g. different package sizes for a frequently purchased product or the number of hotel nights in the current example) is a treatment variable. See Iyengar et al. (2007) for an example of nonlinear pricing involving the sale of cellphone service. Alternatively, one can use different auction methodologies including the reverse auction method to estimate WTP.[15]

4.3 Product line pricing

In this section, we show how the firm can use information about WTP to determine its optimal product mix and product line pricing strategy after allowing for competition. Consider the following hypothetical example from the PC industry. For simplicity, suppose there are two players in the PC notebook market: Dell and Hewlett-Packard (HP). Let's say that in the first period Dell sells one model of notebook (DELL) and Hewlett-Packard also sells one model (HP_C). Furthermore, there are five segments, each of equal size (1 million), whose WTP for the DELL and HP_C notebooks are as shown in Table 2.4, columns 2 and 3, respectively.

Suppose the marginal costs for the DELL and HP_C notebooks are equal ($800 per unit). In addition, Dell and HP set the prices of their models simultaneously in the first period. Consider the following pricing scenario. Let's say that Dell charges a price of $1200 for the DELL notebook and HP charges a price of $1400 for the HP_C model. Then each consumer will choose the notebook model that maximizes her surplus. If the maximum surplus is negative, the consumer will not purchase either model. Given this set of prices, Segments 1 and 2 will purchase the DELL, Segments 3 and 4 will

[15] Internet retailers (e.g. Priceline.com) often sell hotel room nights using the reverse auction methodology. Consequently, bidding information by consumers can be used to infer their WTP for purchasing different quantities of a product.

Table 2.5 Industry equilibrium in the first period

DELL price ($)	HP_C price				
	$900	$1100	$1200	$1400	$1500
900	(250, 250)	(300, 600**)	(350, 600**)	(500, 0)	(500, 0)
1000	(400, 300)	(400, 600)	(400, 800**)	(700, 300)	(800, 0)
1200	(800*, 300)	(800*, 600)	(800, 800)	(800, 1200**)	(800, 1200)
1600	(0, 500)	(800*, 900)	(1600*, 800)	(1600*, 1200**)	(1600, 700)
1700	(0, 500)	(0, 1200)	(450, 1000)	(900, 1200**)	(900, 700)

Notes: All entries in parentheses are in millions of dollars. The first entry denotes DELL's gross profits and the second denotes the gross profits for HP_C.
* optimal policy for Dell model conditional on price chosen by HP.
** optimal policy for HP conditional on price chosen by Dell.

purchase the HP_C model, and Segment 5 will not purchase a notebook. Hence Dell will make a profit of $800 million (= unit margin × number of customers in Segments 1 and 2 combined) and HP will make a profit of $1200 million (= unit margin × number of customers in Segments 3 and 4 combined; see Table 2.5). Similarly, one can obtain the profits for Dell and HP for different sets of market prices. In the example, we assume that, if the consumer surpluses for any segment are zero for both products, half the segment will purchase the HP product and the other half will purchase the DELL model.

Assume that Dell and HP do not cooperate with each other. In Table 2.5, the * notation denotes the optimal price for DELL conditional on any price for HP_C and the ** notation denotes the optimal price for the HP_C notebook conditional on any price for the Dell notebook. Since the firms do not cooperate with each other, in the first period Dell will charge a price of $1600 per notebook and HP will charge a price of $1400 per notebook. (This is the Nash equilibrium.) Given these prices, Dell will make a gross profit of $1.6 billion and HP will make a gross profit of $1.2 billion. See Table 2.5.

Now, consider the second period. For simplicity, assume that Segment 5 (nonpurchasers in the first period) leaves the market in the second period. In addition, a new cohort of consumers enters the market in the second period. These consumers are clones of those in the first period. That is, there are five segments of equal size (1 million each) in the second period with the same set of reservation prices for notebook computers as the corresponding segments in the first period.

Suppose HP has developed a new technology in the second period which allows it to add a new set of product features to its notebook computers. For simplicity, assume that the marginal costs of adding these new features are approximately zero.[16] Suppose Dell does not have the technology to add these new features; in addition, Dell will continue to charge the same price for its DELL model in the second period ($1600 per unit).[17]

[16] This assumption is not an unreasonable approximation since most costs are likely to be developmental.

[17] This assumption can be easily relaxed.

Given HP's new technology, which notebook models should HP sell in the second period and what product line pricing policy should HP use? For simplicity, we assume that HP is considering adding a low-end model and/or a high-end model to its notebook product line. We consider three strategies. One alternative for HP is to continue to sell the old model (HP_C) and to introduce the HP_L model, a low-end notebook (Strategy A). A second alternative is to sell the old model (HP_C) and introduce a high-end notebook, HP_H, aimed at the premium market (Strategy B). A third strategy is to use a 'flanking' strategy (Strategy C). That is, sell a low-end notebook (HP_L) that is of lower quality than the DELL, sell a high-end notebook (HP_H) that is of higher quality than the DELL, and continue selling the old HP model (HP_C).[18]

We begin with Strategy A, where HP augments its product line in the second period by introducing only the low-end notebook. Consumers in the second period now have three choices: they can purchase the old HP model (HP_C), the new low-end HP model (HP_L), or the DELL. As before, consumers will make their purchase decisions to maximize their surpluses: if the maximum surplus from purchase is negative, consumers will not purchase the notebook. Then, following the previous approach, we can show that HP will leave the price of the old model (HP_C) unchanged at \$1400 per unit and charge a price of \$900 per unit for the low-end model. Given these prices in the second period, consumers in Segments 1 and 2 will purchase the DELL and consumers in Segments 3 and 4 will purchase the old HP model (HP_C). However, consumers in Segment 5 will now purchase the low-end HP notebook (HP_L). Note that the new low-end HP model does not cannibalize HP's old product or steal sales from Dell. In particular, the incremental profit to HP (= \$100 million) comes entirely from market expansion since Segment 5 now buys a notebook. Hence, given this product line policy, HP's profits will increase from \$1.2 billion in the first period to \$1.3 billion.

Suppose HP chooses to augment its product line in the second period by introducing only the new high-end PC notebook, HP_H (Strategy B). Then, following the previous method, we can show that the optimal policy for HP is to discontinue the old model and charge \$1500 for the high-end model. Given this product line strategy, Segment 1 will continue to buy the DELL. However, Segments 2, 3 and 4 will buy the high-end HP model. Note that HP gains because of switching from a competitor (Segment 2) and 'good' cannibalization (Segments 3 and 4). Specifically, there are three sources of gain: Segment 2 switches from the DELL to the high-end HP model (additional profit to HP = \$700 million), Segment 3 upgrades to the new high-end HP model (additional profit to HP = \$100 million), and Segment 4 also upgrades to the new high-end HP model (additional profit to HP = \$100 million). Hence HP increases its product line gross profit by \$900 million (= 700 + 100 + 100) from \$1.2 billion to \$2.1 billion.

Finally, suppose HP uses a flanking strategy by simultaneously introducing the low-end and high-end PC notebooks (Strategy C). Now, the optimal policy is to discontinue the old model as in Strategy B. Given this product line strategy, Segments 2, 3 and 4 will purchase the high-end HP notebook and Segment 5 will purchase the low-end HP notebook. Note that, in contrast to the other strategies, there are three sources of

[18] We can show that, in our example, a sequential product introduction strategy is dominated by a simultaneous new product introduction strategy.

gain: switching from DELL (Segment 2), 'good' cannibalization (Segments 3 and 4), and market expansion (Segment 5). Specifically, Segment 2 switches from the DELL to the high-end HP notebook (incremental profit= \$700 million), Segments 3 and 4 upgrade from the old model to the high-end HP notebook (incremental profit= \$200 million), and Segment 5 purchases the low-end HP notebook (incremental profit = \$100 million). Hence HP's product-line profit increases by \$1 billion (= 700 + 200 + 100) from \$1.2 billion in the first period to \$2.2 billion in the second.

These results show that Strategy C is optimal for HP. That is, the optimal product mix for HP in the second period is to discontinue its old notebook and to 'flank' DELL by simultaneously introducing two new notebooks: a low-end model (HP_L) that is of lower quality than DELL and a high-end model (HP_H) that is of higher quality than DELL.

In summary, as this example demonstrates, the firm cannot choose its product mix and product line pricing without knowing the distribution of reservation prices for its products *and* those of its competitors. For additional examples and technical details of how to use reservation price data for product-line pricing, see Jedidi and Zhang (2002).

5. Concluding remarks and directions for future research

What can we conclude about the state of the art in WTP research and what are some useful directions for future research in this area? Managerially, the firm needs to know the joint distribution of consumers' reservation prices (WTP) for its products and those of its competitors. As discussed, this information is necessary for the firm to determine how its new product policy affects cannibalization, market growth and the market shares of competing brands. In addition, the firm can use this information to implement nonlinear pricing plans (e.g. quantity discount policies) and to determine its optimal bundling policy (e.g. choose which products to bundle and determine the optimal prices for the individual products and the bundle).

Methodologically, self-stated WTP are likely to be measured with error, regardless of the type of product (e.g. durable or nondurable). When estimating WTP for a public good that is not sold in the market (e.g. the benefits of an environmental policy to reduce pollution), the researcher may have no alternative but to use a contingent valuation method. If, however, the researcher is interested in measuring the WTP for a private good that is sold in the market (as is the case in most market research studies), a better approach is to use an appropriately designed conjoint study, a choice-based experiment, one of the auction methodologies (e.g. the Vickrey auction or the BDM auction method), or the incentive-aligned conjoint methods (e.g. Ding et al., 2005; Park et al., 2007). Given the current state of knowledge, it is not clear which of these methods is superior in general and, if so, in what context (e.g. measuring the WTP for established products or products that are radically new in the marketplace). Hence a better approach for the market researcher may be to use more than one of the methods mentioned above to measure WTP, then use an objective statistical approach to combine results across methods by choosing appropriate weights for each method (e.g. Jedidi et al., 2003).

Future research should focus on several areas. From an applications viewpoint, research should compare different methods for measuring WTP and evaluate the incremental gains from combining different methods in different contexts. This research is necessary so that managers can choose the optimal research design in a particular context, after evaluating the costs and benefits of different methods for measuring WTP.

Additional research is necessary to develop better measures of how consumers' WTP vary with the quantity of product consumed. These measures are necessary for firms to implement nonlinear pricing strategies (e.g. quantity discount policy). Finally, future methodological research should address the issue of optimal bundling strategies when the firm can use nonlinear pricing plans for the individual products and bundles.

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3 Measurement of own- and cross-price effects

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Abstract

The accurate measurement of own- and cross-price effects is difficult when there exists a moderate to large number of offerings (e.g., greater than five) in a product category because the number of cross-effects increases geometrically. We discuss approaches that reduce the number of uniquely estimated effects through the use of economic theory, and approaches that increase the information contained in the data through data pooling and the use of informative prior distributions in a Bayesian analysis. We also discuss new developments in the use of supply-side models to aid in the accurate measurement of pricing effects.

Introduction

The measurement of price effects is difficult in marketing because of the many competitive offerings present in most product categories. For J brands, there are J^2 possible effects that characterize the relationship between prices and sales. The number of competitive brands in many product categories is large, taxing the ability of the data to provide reliable estimates of own- and cross-price effects. A recent study by Fennell et al. (2003), for example, reports the median number of brands in 50 grocery store product categories to be 15. This translates into 225 own- and cross-effects that require measurement in the demand system.

Structure-imposing assumptions are therefore required to successfully estimate price effects. At one end of the spectrum, a pricing analyst could simply identify subsets of brands that are thought to compete with each other, and 'zero-out' the cross-effects for brands that are assumed not to compete. While this provides a simple solution to the task of reducing the dimensionality of the measurement problem, it requires strong beliefs about the structure of demand in the marketplace. Moreover, this approach does not allow the data to express contrary evidence.

Alternatively, one might attempt to measure directly all J^2 own- and cross-price effects. However, it is quickly apparent that using a general rule of thumb that one should have n data points for each effect-size measured rules out the use of most commercially available data. Using weekly sales scanning data and the rule that $n = 5$ results in the need for 20 years of data in food product categories such as orange juice or brownies. One could also engage in the generation of data through experimental means, using surveys or field experiments. The data requirements, however, remain formidable.

We discuss approaches to measuring price effects that rely on modeling assumptions to (i) reduce the number of the effects being measured; and/or (ii) increase the information available for measurement. We begin with a brief review of economic theory relevant to price effects, and then discuss the use of economic models to measure them. We then turn our attention to approaches that increase the available information. These approaches are Bayesian in nature, with information being available either through prior information or from data pooled from other sources. We provide a brief review of modern Bayesian

methods for pooling data, including the use of hierarchical models, and models that incorporate the price-setting behavior of firms (i.e. supply-side models). We conclude with a discussion of measuring price effects in the presence of dynamic effects and other forms of interactions.

1. Economic models for pricing

According to economic theory, own-price effects should be negative and cross-price effects should be positive for competitive goods. As the price of a brand increases, its own sales should decline. As the price of a competitive brand increases, sales should increase. A commonly encountered problem in the use of regression models for measuring price effects is that cross-effects are often estimated to have the wrong algebraic sign – i.e. they are estimated to be negative when they should be positive. Similarly, but less often, own-price effects are estimated to be positive when they should be negative.

When price effects estimates have erroneous signs and large standard errors, a pricing analyst may be tempted to zero them out and re-estimate the remaining effects as described above. However, doing so imposes strong assumptions about the competitive nature of demand – it means that price of one brand has no effect on another brand, for any price, including zero. While approaches such as Bayesian variable selection (George and McCulloch, 1993) help quantify uncertainty in specification searches (Leamer, 1978) such as this, they require the strong assumptions that some of the effect-sizes have a prior probability of being zero. The assumption of a zero effect is often untenable, especially when deriving estimates from aggregate sales data where at least some customers will react to the price change. So, while the practice of setting coefficients to zero solves the problem of incorrectly signed estimates, it does so by imposing somewhat unbelievable assumptions about the structure of demand.

An alternative approach is to employ economic theory to avoid the direct estimation of the J^2 price effects. As with any theory, the use of an economic model reduces the dimensionality of the effects through model parameters. Economic models of behavior are based on the idea of constrained utility maximization:

$$\begin{aligned} &\operatorname*{Max}_{x} U(x_1, \ldots, x_J) = \sum_{j=1}^{J} \psi_j x_j \\ &\text{subject to} \sum_{j=1}^{J} p_j x_j \leq E \end{aligned} \tag{3.1}$$

where $U(x_1, \ldots, x_J)$ denotes the utility of x_1 units of brand 1, x_2 units of brand 2, . . . and x_J units of brand J. In the specification above, utility takes on an additive form that implies that the brands are perfect substitutes. Moreover, this model assumes that utility increases by a constant amount ψ_j as quantity (x_j) increases (i.e. marginal utility is constant). A consumer maximizes utility subject to the budget constraint where p_j is the unit price of brand j, and E is the budgetary allotment – the amount the consumer is willing to spend.

The solution to equation (3.1) can be shown to lead to a discrete choice model, where all expenditure E is allocated to the brand with the biggest bang-for-the-buck, ψ_j/p_j. Assuming that marginal utility has a stochastic component unobservable to the analyst, i.e. $\psi_j = \bar{\psi}_j \exp(\varepsilon_j)$, leads to the demand model:

$$\begin{aligned}\Pr(x_k > 0) &= \Pr\left(\frac{\psi_k}{p_k} > \frac{\psi_j}{p_j} \text{ for all } j\right) \\ &= \Pr(\ln\psi_k - \ln p_k > \ln\psi_j - \ln p_j \text{ for all } j) \\ &= \Pr(\ln\overline{\psi}_k - \ln p_k + \varepsilon_k > \ln\overline{\psi}_j - \ln p_j + \varepsilon_j \text{ for all } j)\end{aligned} \tag{3.2}$$

The assumption that the error term, ε, is normally distributed leads to a probit model, and the assumption of extreme value errors leads to the logit model. More specifically, if ε is distributed extreme value with location zero and scale σ, then equation (3.2) can be expressed as (McFadden, 1981):

$$\begin{aligned}\Pr(x_k > 0) &= \frac{\exp\left[\dfrac{\ln\overline{\psi}_k - \ln p_k}{\sigma}\right]}{\sum_{j=1}^{J}\exp\left[\dfrac{\ln\overline{\psi}_j - \ln p_j}{\sigma}\right]} \\ &= \frac{\exp[V_k]}{\sum_{j=1}^{J}\exp[V_j]}\end{aligned} \tag{3.3}$$

where V_k can be written as $\beta_{0k} - \beta_p \ln p_k$ with $\beta_p = 1/\sigma$ and the intercept β_{0k} equal to ln $\overline{\psi}_k/\sigma$. Since the sum of all probabilities specified by (3.3) adds up to 1, one of the model intercepts is not identified, and it is customary to set one intercept to zero, leaving $J - 1$ free intercepts and one price coefficient.

Thus the use of an economic model (equations 3.1–3.3) requires J parameters to measure the J^2 own- and cross-price effects. This represents a large reduction in parameters (e.g. from 225 to 15 when $J = 15$) that greatly improves the accuracy of estimates. Given the estimated parameters in equation (3.3), own- and cross-price effects can be computed under the assumption that demand (x) takes on values of only zero or one. With this assumption, we can equate choice probability with expected demand, and we can compute own- and cross-effects as

$$\frac{\partial \ln \Pr_j}{\partial \ln p_j} = -\beta_p(1 - \Pr_j) \quad \text{and} \quad \frac{\partial \ln \Pr_j}{\partial \ln p_k} = \beta_p \Pr_k \tag{3.4}$$

where the former is what economists call own elasticity, and the later is the cross-elasticity. It measures the percentage change in expected demand for a percentage change in price.

Economic models can be used to improve the measurement of own- and cross-price effects in either of two ways. The first is to use the model to suggest constraints for an otherwise purely descriptive model. The second is to directly estimate parameters of the micro economic model, and then use these to measure the price effects.

Using economic theory to constrain descriptive models

Most descriptive models of demand are of log-log or semi-log form. Researchers have extended descriptive models in various ways to achieve more flexible functional forms and to account for uncertainty in the functional form (Kalyanam, 1996; Kalyanam and Shively, 1998). For typical marketing data, where the effective unit of analysis usually

only supplies a limited amount of data, highly flexible descriptive models are especially likely to benefit from constraints derived from economic theory. As we will show, the use of economic theory to derive prior distributions for descriptive models is especially useful in this context. A strong signal in the data can override the implications of economic theory but economic theory will dominate data that are not informative to begin with.

Equation (3.4) suggests a number of constraints on price coefficients that can aid direct estimation of the J^2 own- and cross-price effects using descriptive models. Since β_p is simply the inverse of the scale of the error term, we have $\beta_p > 0$ as $\sigma^2 > 0$, implying that

$$\frac{\partial \ln \Pr_j}{\partial \ln p_j} < 0 \quad \text{and} \quad \frac{\partial \ln \Pr_j}{\partial \ln p_k} > 0 \tag{3.5}$$

Constraints of this type, which we call 'ordinal restrictions', occur frequently in the analysis of marketing data. In addition to demand system estimation, the analysis of survey data and use of conjoint analysis are settings in which it is desirable to constrain coefficients so that they are sensible. In addition to expecting that people would rather pay less than more for an offering, researchers also may want to estimate models where preference for a known brand is preferred to an unknown brand, or that respondents prefer better performance assuming all else is held constant.

Natter et al. (2007) describe a decision support system used by bauMax, an Austrian firm in the do-it-yourself home repair industry, which employs ordinal restrictions to derive own effects with correct (negative) algebraic signs. These effects are used by bauMax to derive optimal mark-down policies for the 60,000 stockkeeping units in its stores. Store profits are reported to have increased by 8.1 percent using the decision support system.

Bayesian statistical analysis (see Rossi et al., 2005) offers a convenient solution to incorporating ordinal constraints in models of demand. In a Bayesian analysis, the analyst specifies a prior distribution for the model parameters that reflects his or her beliefs before observing the data. The prior is combined with the data through the likelihood function to arrive at the posterior distribution:

$$\pi(\theta \mid Data) \propto \pi(Data \mid \theta)\pi(\theta) \tag{3.6}$$

where $\pi(\theta)$ denotes the prior distribution, $\pi(Data|\theta)$ denotes the likelihood function; and $\pi(\theta|Data)$ is the posterior distribution. In a regression model, for example, we have

$$y_i = x_i'\beta + \varepsilon_i; \quad \varepsilon_i \sim Normal(0, \sigma^2) \tag{3.7}$$

and assuming the error terms are normally distributed, the likelihood of the observed data is

$$\pi(Data|\theta = (\beta, \sigma^2)) = \prod_{i=1}^{n} \pi(y_i|x_i, \beta, \sigma^2) = \prod_{i=1}^{n} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[\frac{-(y_i - x_i'\beta)^2}{2\sigma^2}\right] \tag{3.8}$$

where x_i is treated as an independent variable and used as a conditioning argument in the likelihood, and the observations are assumed to be independent given the independent variables x and model parameters, $\theta = (\beta, \sigma^2)$. A prior distribution for the regression coefficients β typically also takes on the form of a normal distribution:

$$\pi(\beta|b, s^2) = \frac{1}{\sqrt{2\pi s^2}} \exp\left[\frac{-(\beta - b)^2}{2s^2}\right] \tag{3.9}$$

where the prior mean, b, and prior variance, s^2, are specified by the analyst. The prior for σ^2 is typically taken to be inverted chi-squared.

Allenby et al. (1995) demonstrate that ordinal constraints can be incorporated into the analysis by specifying a truncated normal prior distribution in (3.9) instead of a normal distribution:

$$\pi(\beta|b, s^2, \textit{ordinal restrictions}) = k\exp\left[\sum_{i=1}^{n} \frac{-(\beta - b)^2}{2s^2}\right] I_{\textit{ordinal restrictions}} \tag{3.10}$$

where k is an integrating constant that replaces the factor $1/\sqrt{2\pi s^2}$ in equation (3.9), I is an indicator function equal to one when the ordinal constraints are satisfied, and the parameters b and s^2 are specified by the analyst. Examples of ordinal constraints are that an own-price coefficient should be negative, or that a cross-price coefficient should be positive.

From (3.6), the posterior distribution obtained from the likelihood (equation 3.8) and truncated prior (equation 3.10) is:

$$\pi(\theta|Data) \propto \pi(Data|\theta)\pi(\theta) I_{\textit{ordinal restrictions}} \tag{3.11}$$

which is the truncated version of the unconstrained posterior. Thus the incorporation of ordinal constraints in an analysis is conceptually simple. The difficulty, until recently, has been in making equation (3.11) operational to the analyst. Analytical expressions for the posterior mean and associated confidence, or credible intervals for the posterior distribution, are generally not available.

Markov chain Monte Carlo (MCMC) estimation offers a tractable approach to working with the truncated posterior distribution in (3.11). The idea is to replace difficult analytic expressions with a series of simple, iterative calculations that result in Monte Carlo draws from the posterior. A Markov chain is constructed with stationary distribution equal to the posterior distribution, allowing the analyst to simulate draws from the posterior. These draws are then used to characterize the posterior distribution. For example, the posterior mean is estimated by taking the mean of the simulated draws from the posterior. Confidence intervals and standard deviations are evaluated similarly.

An important insight about simulation-based methods of estimation (e.g. MCMC) is that once a simulator is developed for sampling from the unconstrained parameter distribution (equation 3.6), it is straightforward to sample from the constrained distribution (equation 3.11) by simply ignoring the simulated draws that do not conform to the restrictions. This is a form of rejection sampling, one of many tools available for generating draws from non-standard distributions.

Economic theory can also be used to impose exact restrictions on own- and cross-price effects. Consider, for example, the constraints implied by equation (3.4). A total of $J^2 - J$ constraints is implied by equation (3.4) because there are J^2 own- and cross-price effects and just J parameters in the logit model in (3.3). One set of constraints is related to the well-known independence of irrelevant alternative (IIA) constraints of logit models. The IIA constraint is typically derived from the logit form in (3.3), where the ratio of choice probabilities of any two brands (e.g. i and j) is unaffected by other brands (e.g. k). Thus

changes in the price of brand k must draw proportionally equal choice probability share from brands i and j.

The IIA property is also expressed in equation (3.4) by realizing that the elasticity of demand for brand j with respect to the price of brand k (i.e. η_{jk}) takes the form:

$$\eta_{jk} = \frac{\partial \ln \Pr_j}{\partial \ln p_k} = \beta_p \Pr_k \quad \text{implying} \quad \eta_{jk} = \eta_{ik} = \ldots = \eta_{Jk} | j \neq k \tag{3.12}$$

Thus the change in the price of brand k has a proportionately equal effect on all other choice probabilities. Equation (3.12) implies a 'proportional draw' property for cross-price effects. In a similar manner it can be shown (see Allenby, 1989) that

$$\frac{\eta_{jk}}{\eta_{ji}} = \frac{\Pr_k}{\Pr_i} \tag{3.13}$$

indicating that the magnitude of price elasticity is proportional to the choice probability. Equation (3.13) implies a 'proportional influence' property where an individual's choice probability is influenced more by price changes of the brands they prefer. At an aggregate level, this implies that brands with greater market share have greater influence.

The constraints implied by equations (3.12) and (3.13) can be incorporated into descriptive regression models either by direct substitution or through the use of a prior distribution. Direct substitution imposes the constraints exactly, and a prior distribution provides a mechanism for stochastically imposing the constraints. For example, in analysis of aggregate data, one could substitute a brand's average market share (m) for the choice probability, and reduce the number of parameters in a regression model by using equation (3.13):

$$\begin{aligned} \ln m_{jt} &= \beta_{0j} + \eta_{jj} \ln p_{jt} + \eta_{jk} \ln p_{kt} + \eta_{ji} \ln p_{it} + \cdots \\ &= \beta_{0j} + \eta_{jj} \ln p_{jt} + \eta_{jk} \left(\ln p_{kt} + \frac{m_i}{m_k} \ln p_{it} + \cdots \right) \end{aligned} \tag{3.14}$$

where t is an index for time. A more formal and flexible approach is to employ a prior distribution that stochastically constrains model parameters to lie close to the subspace implied by the restrictions. Restrictions on the own- and cross-price effects can be expressed as functions of parameters, and priors can be placed on their functional values. To express the equality in equation (3.12), which is equivalent to $\eta_{1k} - \eta_{2k} = \ldots = \eta_{1k} - \eta_{Jk}$, a contrast matrix, R, is used:

$$R = \begin{bmatrix} 1 & -1 & 0 & \cdots \\ 1 & 0 & -1 & \cdots \\ \vdots & \vdots & \cdots & \vdots \\ 1 & 0 & \cdots & -1 \end{bmatrix} \tag{3.15}$$

If equation (3.12) holds exactly, the product $R\eta$ with $\eta = (\eta_{1k}, \ldots \eta_{Jk})$ is a vector of zeros and a prior centered on this belief can be expressed using a normal distribution with mean zero:

$$\pi(R\eta) = (2\pi)^{-(J-1)/2} |S|^{-1/2} \exp\left[-\frac{1}{2} (R\eta) S^{-1} (R\eta)' \right] \tag{3.16}$$

An advantage of this approach is that the prior distribution can be used to control the precision of the restriction through the variance–covariance matrix S.

Montgomery and Rossi (1999) use such an approach to impose restrictions on price elasticities in a descriptive model of demand. This approach assumes that the prior distribution can be constructed with measures that are (nearly) exogenous to the system of study. This assumption is also present in equation (3.14) when employing average market shares, m_i, to impose restrictions. It is reasonable when there are many brands in a category, such that any one brand has little effect on the aggregate expenditure elasticity for the category, when there are sufficient time periods so that the average market share for a brand is reliably measured and when there are no systematic movements in the shares across time.

Formal approaches to demand estimation

The use of linear models to estimate own- and cross-price effects has a long history in economics. Linearity, however, has been limiting research to a restricted number of utility functions. Demand functions, in general, are derived by solving for the demand that maximizes utility subject to the budget (i.e. income) constraint. For the Cobb–Douglas utility function, the demand function can be shown to be of log-log form where the logarithm of quantity is a linear function of logarithm of income and logarithm of price (Simon and Blume, 1994, Example 22.1). Other utility functions do not result in demand functions that are easily estimable with OLS (ordinary least squares).

Some analysts elect to start with the indirect utility function rather than the utility function. The indirect utility function is defined as the maximum utility attainable for a given set of prices and expenditure. It can be shown that differentiating the indirect utility function using Roy's identify (see Simon and Blume, 1994, Theorem 22.5) leads to the demand equation in which demand is expressed as a function of price and income. Varian (1984, ch. 4) demonstrates that this approach usually leads to demand functions that are nonlinear. Some indirect utility functions, such as the translog function of Christensen et al. (1975), lead to linear systems for estimation if a representative economic agent is assumed and consumer heterogeneity is thus ignored. Integrating over a distribution of heterogeneity results in a nonlinear specification that requires the use of alternative methods of estimation (see Allenby and Rossi, 1991 for an exception).

A direct approach to demand estimation is to derive the likelihood of the data corresponding to constrained utility maximization. Distributional assumptions are made about stochastic errors that enter the utility function, understood as information known to the consumer but not observed by the analyst, and from these primitive assumptions the likelihood is derived. Kim et al. (2002) provide an example of such an approach, where utility is specified with diminishing marginal returns:

$$\begin{aligned} &\max_x U(x_1, \ldots, x_J) = \sum_{j=1}^{J} \psi_j (x_j + \gamma_j)^{\alpha_j} \\ &\text{subject to } \sum_{j=1}^{J} p_j x_j \leq E \end{aligned} \tag{3.17}$$

Here, γ_j translates the utility function to allow for corner and interior solutions. Diminishing marginal returns occur if α_j is positive and less than one. The likelihood is

obtained by differentiating the Lagrangian $U(x) - \lambda(p'x - E)$ to obtain the Kuhn–Tucker (KT) conditions as follows:

$$\frac{\partial U}{\partial x_1} - \lambda p_1 = \ldots = \frac{\partial U}{\partial x_J} - \lambda p_J = 0, \text{ that is, } \frac{\partial U}{\partial x_1}\frac{1}{p_1} = \ldots = \frac{\partial U}{\partial x_J}\frac{1}{p_J} = \lambda$$

where $\partial U/\partial x_j = \psi_j \alpha_j (x_j + \gamma_j)^{\alpha_j - 1}, j = 1, \ldots J$. Assuming that log marginal utility can only be measured up to additive error, i.e. $\ln\psi_j = \ln\overline{\psi}_j + \varepsilon_j$, and that the observed data conform to the KT conditions, we have for both x_i and x_j positive:

$$\ln(\overline{\psi}_i \alpha_i (x_i + \gamma_i)^{\alpha_i - 1}) - \ln p_i + \varepsilon_i = \ln(\overline{\psi}_j \alpha_j (x_j + \gamma_j)^{\alpha_j - 1}) - \ln p_j + \varepsilon_j \quad (3.18)$$

or

$$(\ln(\overline{\psi}_i \alpha_i (x_i + \gamma_i)^{\alpha_i - 1}) - \ln p_i) - (\ln(\overline{\psi}_j \alpha_j (x_j + \gamma_j)^{\alpha_j - 1}) - \ln p_j) = \varepsilon_j - \varepsilon_i \quad (3.19)$$

Equation (3.19) provides a basis for deriving the likelihood of the data, $\pi(Data|\theta = (\overline{\psi}, \alpha, \gamma))$ through the distribution of $(\varepsilon_j - \varepsilon_i)$. The distribution of the observed data $\{x_i, x_j\}$ is obtained as the distribution of the calculated errors $\{\varepsilon_i, \varepsilon_j\}$ multiplied by the Jacobian of the transformation from ε to x. Modern Bayesian (MCMC) methods are well suited to estimate such models because they require the evaluation of the likelihood only at specific values of the parameters, and do not require the evaluation of gradients or Hessians of the likelihood. Once the parameters of the utility function are available, estimates of own- and cross-effects can be obtained by solving equation (3.17) numerically for various price vectors and computing numeric derivatives.

Standard discrete choice models such as multinomial logit and probit models are the simplest examples of the direct approach. Utility is assumed to take a linear form with constant marginal utility (equation 3.1), and random error is introduced as shown in equation (3.2). Constant marginal utility implies that as income increases consumers simply consume more of the same brand rather than switching to a higher-quality brand. Allenby and Rossi (1991) use a non-constant marginal utility (non-homothetic), which motivates switching from inferior goods to superior goods as income increases. As a consequence, price responses are asymmetric. Price changes of high-quality brands have a higher impact on low-quality brands than vice versa (see Blattberg and Wisniewski, 1989 for a motivation of asymmetric price response based on heterogeneity).

Chiang (1991) and Chintagunta (1993) remove the 'given purchase' condition inherent to discrete choice models and model purchase incidence, brand choice and purchase quantity simultaneously through a bivariate utility function. A generalized extreme value distribution implies both a probability to purchase and a brand choice probability. A flexible translog indirect utility function is maximized with respect to quantity given a brand is purchased. Variants of this approach have been used by Arora et al. (1998), Bell et al. (1999), and Nair et al. (2005).

The translog approach results in price effects that can be decomposed into three parts: changes in purchase probability, changes in brand choice given purchase occurrence; changes in purchase quantity given purchase occurrence and brand selection. Bell et al. (1999) show that these three components are influenced in different ways by exogeneous consumer-, brand- and category-specific variables.

The linear additive utility specification popular in marketing implies that all brands are perfect substitutes, so that only one brand is chosen as the utility-maximizing solution. Nonlinear utility functions such as (3.17) allow for both corner and interior solutions. That is, a consumer chooses one alternative or a combination of different alternatives as the result of utility maximization. Thus the model quantifies the tradeoff between price and the variety of the product assortment (see Kim et al., 2002, 2007 for details). A different form of nonlinear utility function is used by Dubé (2004), who motivates the choice of more than one brand by multiple consumption occasions that are considered during a customer's shopping trip.

2. Improving measurement with additional information

An alternative to constraining and/or reducing the parameter space through the use of economic models is to use approaches that attempt to increase the available information for estimation. We investigate two approaches to data pooling. The first is with the use of random-effects models that effectively borrow information from other similar units through the random-effects distribution. The second approach pools information from the supply side. This approach views the prices themselves as endogenous to the system of study, and models are specified as a system of demand and supply equations. Both approaches have become practical in applications with the advent of modern Bayesian methods.

Pooling across units

Random-effects models add another layer to the Bayesian prior distribution. Equation (3.9) is the prior associated with one unit of analysis, where the unit might be sales at a specific retailer or in a specific geographic region. When multiple units of analysis are available, it is possible to pool the data by specifying a relationship among the model parameters:

$$\begin{aligned} &\pi(Data_i|\theta_i) \quad \text{for } i = 1, \ldots, N \\ &\pi(\theta_i|\zeta) \\ &\pi(\zeta) \end{aligned} \tag{3.21}$$

where ζ are known as hyper-parameters – i.e. parameters that describe the distribution of other parameters. For example, $\pi(Data_i|\theta_i)$ could represent a time-series regression model for sales of a specific brand in region i, with own- and cross-effects coefficients θ_i. The second layer of the model, $\pi(\theta_i|\zeta)$, is the random-effects model. A commonly assumed distribution is multivariate normal. Finally, the third layer, $\pi(\zeta)$, is the prior distribution for the hyper-parameters.

Pooling occurs in equation (3.21) because θ_i is present in both the first and second equations of the model, not just the first. The data from all units are used to inform the hyper-parameters, and as the accuracy of the hyper-parameter estimates increases, so does that of the estimates of the individual-level parameters, θ_i. The posterior distribution of the hierarchical model in (3.21) is

$$\pi(\{\theta_i\}, \zeta | \{Data_i\}) \propto \prod_{i=1}^{N} \left(\prod_{t=1}^{T_i} \pi(Data_{it}|\theta_i) \right) \pi(\theta_i|\zeta)\pi(\zeta) \tag{3.22}$$

which highlights a key difference between the Bayeisan and non-Bayesian treatment of random-effects models. In a Bayesian treatment, the posterior comprises the hyper-parameters and all individual-level parameters. In a non-Bayesian treatment, parameters are viewed as fixed but unknown constants, the analysis proceeds by forming the marginalized likelihood of the data:

$$\pi(\{Data_i\}|\zeta) = \prod_{i=1}^{N}\int\left(\prod_{t=1}^{T_i}\pi(Data_{it}|\theta_i)\right)\pi(\theta_i|\zeta)d\theta_i \tag{3.23}$$

The Bayesian treatment does not remove the individual-level parameters from analysis, and inferences about unit-specific parameters are made by marginalizing the posterior distribution in equation (3.22):

$$\pi(\theta_i|\{Data_i\}) = \int\pi(\{\theta_i\},\zeta|\{Data_i\})\,d\{\theta_{-i},\zeta\} \tag{3.24}$$

Modern Bayesian methods deliver the marginal posterior distribution of model parameters at no additional computational cost. The MCMC algorithm simulates draws from the full posterior distribution of model parameters in (3.22). Analysis for a particular unit, θ_i, proceeds by simply ignoring the simulated draws of the other model parameters, θ_{-i} and ζ. Thus the hierarchical model, coupled with modern Bayesian statistical methods, offers a powerful and practical approach to data pooling to improve parameter estimates.

Allenby and Ginter (1995), and Lenk et al. (1996) demonstrate the efficiency of the estimates obtained from the hierarchical Bayes approach in comparison with the traditional estimation methods. The number of erratic signs on price-elasticity estimates is significantly reduced as more information becomes available via pooling. Montgomery (1997) uses this methodology to estimate store-level parameters from a panel of retailers. Ainslie and Rossi (1998) employ a hierarchical model to measure similarities in demand across categories. Arora et al. (1998) jointly model individual-level brand choice and purchase quantity, and Bradlow and Rao (2000) model assortment choice using hierarchical models.

Bayesian pooling techniques have found their way into practice through firms such as DemandTec (demandtec.com), who specialize in retail price optimization. Current customers of DemandTec include Target, WalMart and leading grocers such as Safeway and Giant Eagle. A major challenge in setting optimal prices at the stockkeeping unit level is the development of demand models that accurately predict the effects of price changes on own sales and competitive sales. Retailers want to set prices to optimize profits in a product category, and a critical element involves estimating coefficients with correct algebraic signs (i.e. own-effects are negative, cross-effects are positive) so that an optimal solution exists. For example, if an own-effect is estimated to be positive, it implies that an increase in price is associated with an increase in demand, and the optimal price is therefore equal to positive infinity. This solution is neither reasonable nor believable. DemandTec uses hierarchical Bayesian models such as equation (3.21) to pool data across similar stockkeeping units to help obtain more accurate price effects with reasonable algebraic signs.

Another industry example of the use of hierarchical Bayesian analysis is Sawtooth Software (sawtoothsoftware.com), the leading supplier of conjoint software. Conjoint

analysis is a popular quantitative technique used to evaluate consumer utility for attribute levels, and express them in terms of a common metric. For example, consumer preference for different credit cards can be viewed in terms of utility for different interest rates, grace periods, annual fees, etc. Conjoint analysis estimates the part-worths of the levels of these attributes. In most studies, price is specified as an attribute, and consumer price-sensitivity (β_p) is measured at the individual-respondent level using a hierarchical model. The individual-level estimates are then used to predict changes in demand for all products in a category in response to changes in product attributes, including price. Data pooling via a hierarchical model structure is critical for obtaining individual-level part-worths because of the limited number of conjoint questions that can be asked of a respondent in an interview. Sales for the hierarchical Bayes version of Sawtooth's conjoint software now dominates their non-Bayesian version.

Incorporating supply-side data

Up to this point we have considered models where prices are viewed as explanatory of sales, and also independently determined. This assumption is acceptable when analyzing survey and experimental data because prices are set by the analyst. However, when data are from the marketplace, prices are set in anticipation of demand and profits. Observed prices are influenced by the preferences and sensitivities of consumers, the same factors (e.g. utility function parameters) that influence the magnitude of the own- and cross-price effects.

When explanatory variables are endogenously determined, the likelihood will comprise multiple equations that form a system of equations. Exceptions to this general rule are discussed by Liu et al. (2007). As discussed in the use of formal economic models above, the key in conducting analysis of simultaneous equation systems is to relate primitive assumptions about how errors enter the model to the likelihood for the observed data.

Consider, for example, a monopolist pricing problem using a constant elasticity model, where it is assumed that the variation in prices over time is due to stochastic departures from optimal price-setting behavior. The likelihood for the data is a combination of a traditional demand model:

$$\ln y_t = \beta_0 + \beta_1 \ln p_t + \varepsilon_t; \quad \varepsilon_t \sim Normal(0, \sigma_\varepsilon^2) \tag{3.25}$$

and a factor for the endogenous price variable. Optimal pricing for the monopolist can be shown to be (see for example, Pashigian, 1998, p. 333):

$$p_t = mc\left(\frac{\beta_1}{1 + \beta_1}\right)e^{\upsilon_t}; \quad \upsilon_t \sim Normal(0, \sigma_\upsilon^2) \tag{3.26}$$

where *mc* denotes the marginal cost of the brand, and a supply-side error term has been added to account for temporal variation of observed prices from the optimal price. Taking logs of equation (3.26) yields

$$\ln p_t = \ln mc + \ln\left(\frac{\beta_1}{1 + \beta_1}\right) + \upsilon_t; \quad \upsilon_t \sim Normal(0, \sigma_\upsilon^2) \tag{3.27}$$

Equations (3.25) and (3.27) form a system of equations that effectively pools supply-side information and improves the estimation of the own-price effect, β_1, if the marginal cost

of the brand is known. That is, the average level of price is informative about β_1 given marginal cost. The likelihood for equations (3.25) and (3.27) is obtained by solving for error terms:

$$\begin{aligned} \varepsilon_t &= \ln y_t - \beta_0 - \beta_1 \ln p_t \sim Normal(0, \sigma_\varepsilon^2) \\ \upsilon_t &= \ln p_t - \ln mc - \ln\left(\frac{\beta_1}{1+\beta_1}\right) \sim Normal(0, \sigma_\upsilon^2) \end{aligned} \tag{3.28}$$

and computing:

$$\begin{aligned} \pi(Data|\theta) &= \prod_{t=1}^{T} \pi(y_t, p_t | \beta_0, \beta_1, \sigma_\varepsilon^2, \sigma_\upsilon^2) \\ &= \prod_{t=1}^{T} \pi(\varepsilon_t, \upsilon_t | \beta_0, \beta_1, \sigma_\varepsilon^2, \sigma_\upsilon^2) \times J_{(\varepsilon_t, \upsilon_t) \to (y_t, p_t)} \\ &= \prod_{t=1}^{T} \pi(\varepsilon_t, \upsilon_t | \beta_0, \beta_1, \sigma_\varepsilon^2, \sigma_\upsilon^2) \times \frac{1}{y_t p_t} \end{aligned} \tag{3.29}$$

In this example, the supply-side equation offers additional information that is useful for estimating the own-price effect in two ways. The first way, as mentioned above, is to help locate the value of β_1 if marginal cost is known. The second way is through an ordinal constraint imposed by the supply-side model – i.e. $\beta_1 < -1$ for the supply equation to be valid. If $-1 \leq \beta_1 < 0$, $\beta_1/(1+\beta_1)$ is negative, equation (3.26) no longer yields the price that maximizes profits and thus the logarithm in equation (3.27) is not defined. Optimal pricing behavior with positive, finite prices exists only when own-price effects are elastic. Thus the supply-side equation constrains the estimates of price effects by merely ascertaining that optimal pricing with positive, finite prices is possible. This aspect of supply-side analysis is investigated in more detail by Otter et al. (2007).

When the error terms, ε_t and υ_t, are correlated, analysis without the supply side leads to inconsistent estimates (Besanko et al. 1998; Villas-Boas and Winer, 1999). The typical rational for correlated demand- and supply-side shocks is the presence of a common omitted variable that raises prices and demand at the same time – e.g. a retailer correctly anticipates a demand shock and simultaneously raises prices. Thus the presence of endogenous price variation requires joint estimation of demand- and supply-side equations to obtain consistent estimates of own- and cross-price effects.

Supply-side equations may be reduced-form linear models (Villas-Boas and Winer, 1999), or structural models where the supply-side equations are obtained through maximizing objective functions of firms and/or retailers. For example, Sudhir (2001a) obtains the supply-side pricing equations by assuming that the firm maximizes the sum of own profits and weighted competitor profits, where the weight on competitor profits characterizes cooperative (positive weight) or aggressive (negative weight) competitive behavior. Chintagunta (2002) obtains the supply-side pricing equations by assuming that retailers set prices to maximize a weighted sum of category profits and store brand share while accounting for manufacturers' actions, store traffic effects and retail competition. Chintagunta and Desiraju (2005) obtain supply-side equations by maximizing a profit function that accounts for firm interactions within a geographic market as well as interactions across all geographic markets. Other examples of structural supply-side models

include Besanko et al. (1998), Sudhir (2001b), Draganska and Jain (2004) and Villas-Boas and Zhao (2005).

Techniques to obtain parameter estimates in demand- and supply-side equations include generalized method of moments (GMM) estimation using instrumental variables (see Berry, 1994; Berry et al., 1995; and Nevo, 2001), maximum likelihood estimation (see Villas-Boas and Winer, 1999; Villas-Boas and Zhao, 2005; and Draganska and Jain, 2004), and the Bayesian approach (see Yang et al., 2003).

3. Concluding comments

The measurement of own- and cross-price effects in marketing is complicated by many factors, including a potentially large number of effects requiring measurement, heterogeneity in consumer response to prices, the presence of nonlinear models of behavior, and the fact that prices are set strategically in anticipation of profits by manufacturers and retailers. Over the course of the past 20 years, improvements in statistical computing have allowed researchers to develop new models that improve the measurement of price effects.

The measurement of price effects is inextricably linked to choice and demand models, and more generally consumer decision-making. These are very active research areas, and the implications of many of the more recently published choice models for the measurement of price effects and price setting have yet to be explored. In this chapter we focused on static models that imply (only) an immediate and continuous price response. There is active research on dynamic price effects. Dynamic price effects refer to the effects of price change on future sales as mediated by stockpiling and/or increased consumption. Effects to be measured include immediate, future and cumulative (immediate + future) effects of promotional and/or regular price changes, which may differ in sign and magnitude. For example, as shown by Kopalle et al. (1999), promotions have positive immediate effects but negative future effects on baseline sales. Autoregressive descriptive demand models (see, e.g., Kopalle et al., 1999; Fok et al., 2006) and utility-based demand models (Erdem et al., 2003) have recently been used to account for carry-over effects from past discounts, forward-looking consumer behavior and competitive price reactions. The same approaches are taken to dealing with measurement difficulties – using theory to impose restrictions on parameters, Bayesian pooling, and adding supply-side information.

Finally, there is a large behavioral literature documenting the influence of consumer cognitive capacity, memory, perceptions and attitudes in reaction to price (see Monroe, 2002 for a review). An active area of current research develops demand models that incorporate such behavioral decision theory for an improved measurement of price effects (Gilbride and Allenby, 2004, 2006).

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4 Behavioral pricing

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Abstract

The focus is on 'behavioral aspects of pricing', or price effects that cannot be accounted for by the intrinsic price itself. After presenting a broad conceptual framework, I concentrate on two distinct streams of research. The first is composed of laboratory experiments examining the impact of price presentation (e.g. externally provided reference price, whether a deal is presented in absolute dollars off or in percentage off the original price) on perceived price savings. The second stream uses secondary data on consumer purchases (scanner data) and focuses on the effects of internal reference prices, reference prices that are created by consumers themselves, on consumer purchase behavior.

Introduction

Victoria's Secret frequently advertises 'Buy two, get one free'. Storewide sales in Talbots, The Gap, Benetton and others are often announced by signs proclaiming '20–50% off' or 'Up to 70% off'. Are price cuts presented in different ways perceived differently by consumers? If the consumer rationally computes his (her) savings, mental effort could be reduced by simply stating the dollar savings to the consumer. Yet, apparently, the presentation of the promotion has an impact on consumer deal evaluation and hence retail sales. In fact, much research in marketing attests to the effect of price presentation on deal perception (Das, 1992; Lichtenstein and Bearden, 1989; Urbany et al., 1988; Yadav and Monroe, 1993). Non-rational (in the traditional sense) processing of price information is further attested to by Inman et al.'s (1990) finding that the mere presence of a sale announcement, without a reduced price, increased retail sales. Hence, an understanding of price presentation effects is insightful for retailers as well as for brand managers.

In similar vein, if a consumer is fortunate in frequenting a store multiple times when a particular brand is on sale, and then visits the store when it is not on sale, will she be less likely to purchase it – i.e. will the fact that she has purchased the product at a lower price in the past reduce her probability of buying it at regular price in the future? What if she has bought it at regular price for many shopping trips, and now finds it on sale? Will her probability of purchasing the brand increase by the same extent as it would decrease in the previous scenario? Comprehension of internal reference price effects – reference prices that are created by consumers themselves – is important when deciding on price changes over time.

In this chapter, we focus on 'behavioral aspects of pricing' or price effects that cannot be accounted for by the intrinsic price itself. After presenting a broad conceptual framework, we concentrate on two distinct streams of research, price presentation effects and internal reference price effects, that have just been illustrated. The first typically uses laboratory experiments, whereas the second uses secondary data on consumer purchases (scanner data). For price presentation effects, we report results from a meta-analysis (Krishna et al., 2002) where results from past literature are examined to determine the relative importance of different presentation effects (Section 2). For internal reference

price effects, we provide a summary of the papers that have been contributed in that area (Section 3). We begin with the framework.

1. Conceptual framework

While much research in marketing and economics has focused on the effect of intrinsic price, only in the last three decades has research focused on behavioral aspects of pricing. However, the latter can be just as significant for consumer choice. We identify a few of the behavioral aspects of special relevance to marketing researchers. By no means is this meant to be an exhaustive review of the literature. Figure 4.1 illustrates our conceptual framework.

The final dependent variables in our conceptual framework are consumer choice among brands, purchase quantity and purchase timing. Two other intermediary dependent variables are identified – subjective price and price fairness. Subjective price is assumed to be affected by many factors, as can be seen in Figure 4.1. Price fairness has also been attributed with many antecedents. We talk about each in turn.

Subjective price

We elaborate in detail on price presentation effects (through a published meta-analysis) and on internal reference price effects in Sections 2 and 3. However, two other price presentation effects not included in the meta-analysis are worthy of mention – these are the effects of (i) '99 cent endings and (ii) temporal pricing and partitioned prices.

99 cent endings Schindler and Kirby (1997) made an analysis of the rightmost digits of selling prices in retail advertisements and found an overrepresentation of 0, 5 and 9. Using the same historical data, they show that this practice cannot be explained by consumers perceiving 9-endings as a round-number price with a small amount given back; instead, it is better explained by underestimation of 9-ending prices with left-to-right processing. Stiving and Winer (1997) provide further proof for the additional utility of 9-endings. Using scanner panel data, they show that 9-ending prices do indeed have additional utility for consumers and that predictive models need to account for this effect for more accuracy.

Temporal pricing and partitioned prices Another area of behavioral pricing research where many puzzles remain unresolved is that of partitioned pricing and temporal pricing. Gourville (1998) shows in his paper that pennies-a-day pricing is a better appeal to consumers for charitable donations than a larger amount paid per month. Similarly, Morwitz et al. (1998) show that separating the total price of a product into the base price and shipping charge is better than presenting it as one combined price. In both the temporal-price-framing case (Gourville, 1998) and the partitioned pricing case, consumers are being asked to pay a larger number of smaller dollar amounts, and this is found to be better valued by consumers. These cases go against Thaler's (1985) segregate losses rule. One explanation may be that very tiny amounts are ignored by consumers – in the pennies-a-day case, all payments are deemed trivial, and in the partitioned pricing case, the shipping charge is small in comparison with the base price and is ignored. Thus, Thaler's arguments do not extend to these cases. Such a hypothesis nevertheless needs further research.

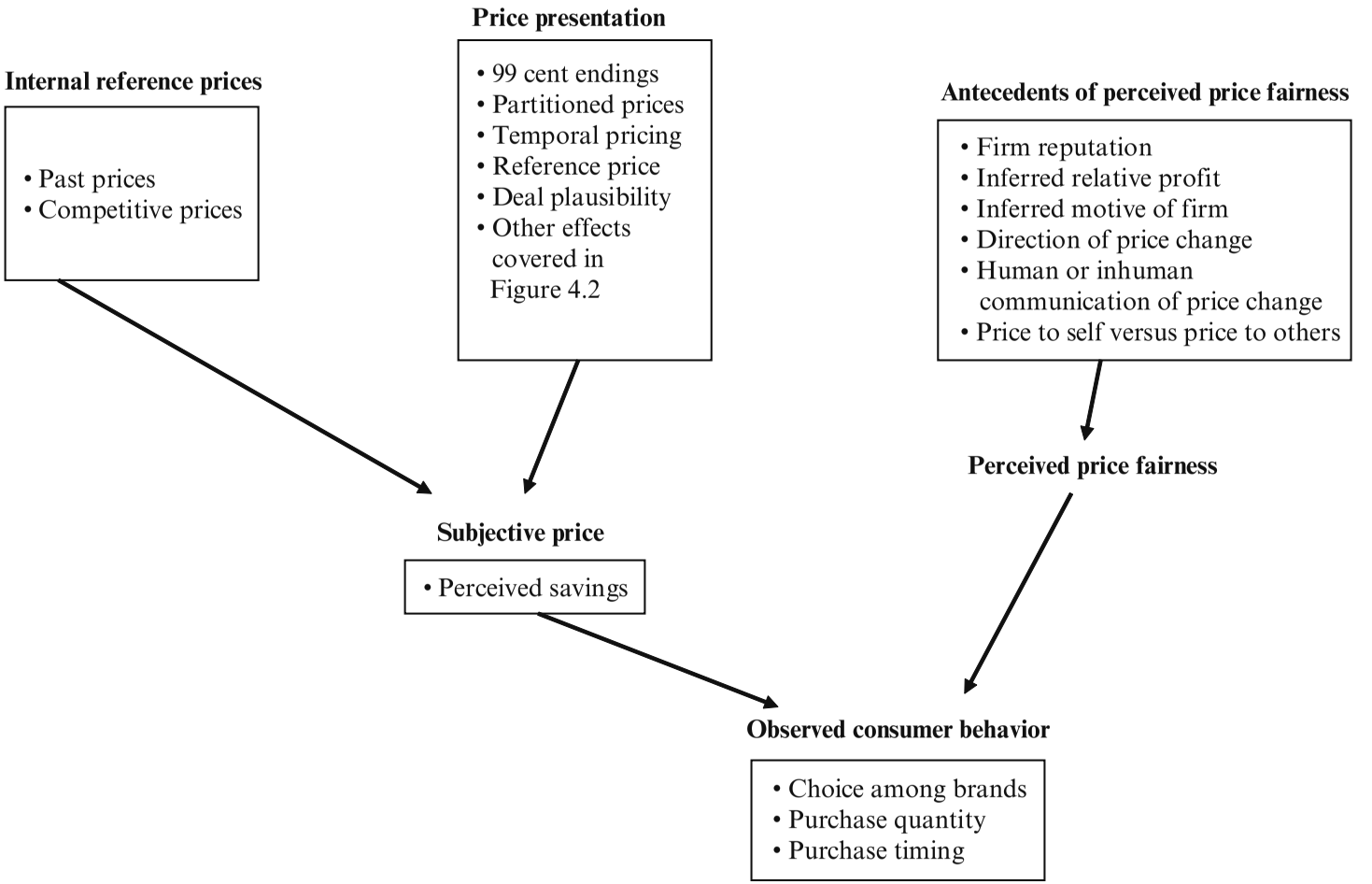


Figure 4.1 Conceptual framework

Price fairness

Campbell (1999) provides a rigorous structure for the antecedents and consequences of perceived price fairness. She sets up a scenario where a firm intends to sell a doll by auction just before Christmas because of its rarity. The auction implies a sudden price change (i.e. price increase) compared to the doll's normal market price. Campbell shows in this context that the auction is perceived as more unfair when the firm actually makes more profit than it normally does. Furthermore, when consumers impute a negative motive to the firm (e.g. the firm is making extra profit), the auction is perceived as significantly less fair than the same auction when the firm's motive is seen as positive (e.g. the money is going to a charity). Furthermore, firms with good reputations are more likely to be given the benefit of the doubt by consumers about their motive. More recently, Campbell (2007) further studies the antecedents of price (un)fairness by incorporating the effects of the source of price information and affect on consumers' perceived price (un) fairness. The research shows that whether the price change (increase or decrease) is communicated by human or nonhuman means (e.g. price tag) moderates consumers' fairness perception. This is because the imputed motive of the marketer and affect elicited by such price information both mediate the effect of the price change.

Other authors have studied the effects of perceived price unfairness arising from targeted pricing whereby firms offer different prices to different consumers. Krishna and Wang (2007) demonstrate experimentally that consumers will leave money rather than interact with firms that are perceived to engage in targeted pricing that is believed to be unfair. Feinberg et al. (2002) show that, in this context, the competitive equilibrium will not necessarily be one where firms offer lower prices to new customers to attract them, but can be one where firms offer lower prices to old customers to retain them. Krishna et al. (2007) find a similar result in the context of increasing prices where a constant price is perceived as a deal. Most competitive models in marketing are based on the assumption that consumers are rational utility-maximizers who are motivated only by 'self-regarding preferences'. That is, they care only about their own payoffs. In the papers incorporating fairness, it is shown that consumer behavior may also be affected by 'social preferences'.

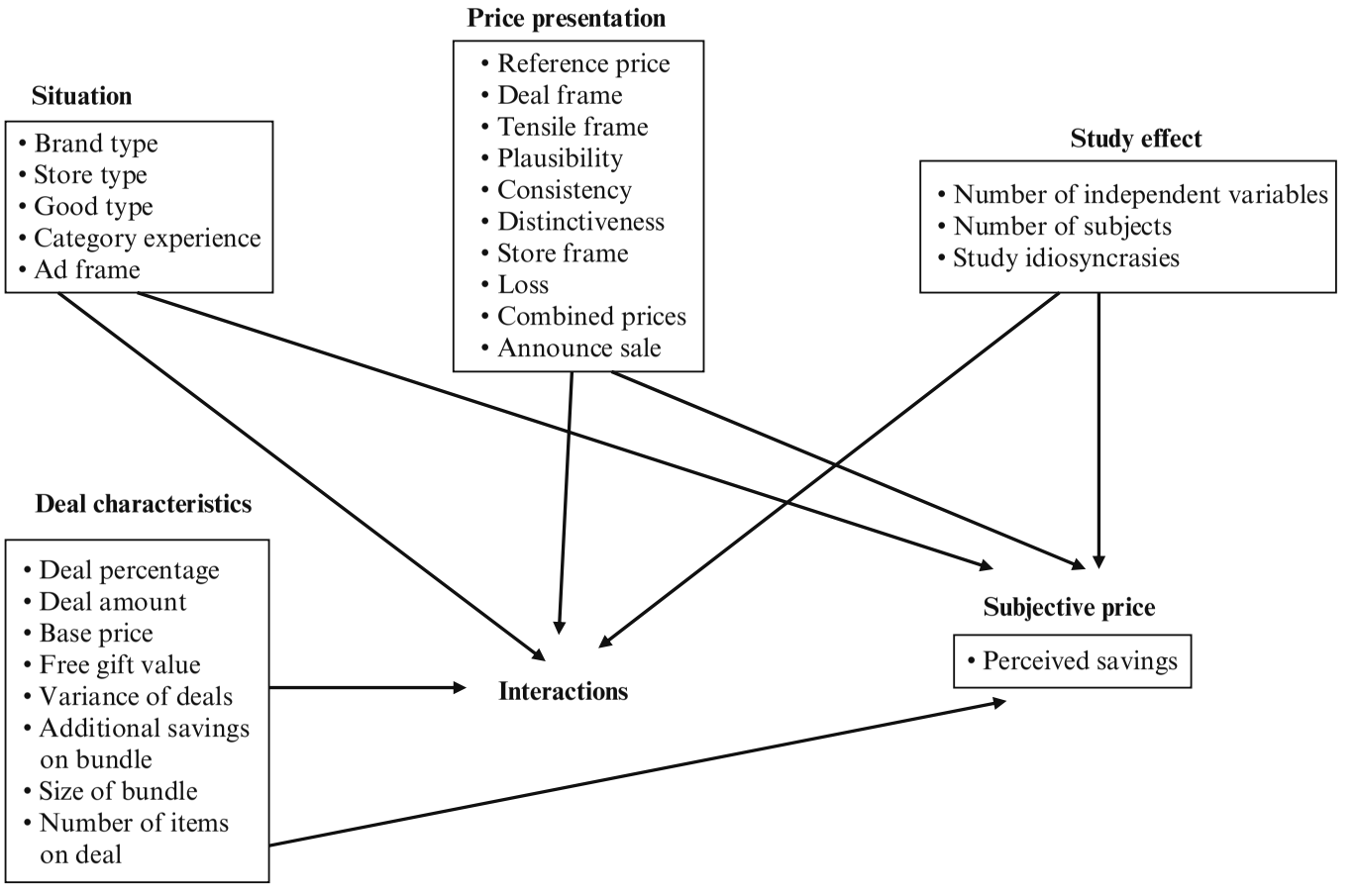
We now discuss the meta-analysis of price presentation effects.

2. Meta-analysis of price presentation effects[1]

Krishna et al. (2002) offer a fairly broad meta-analysis of price presentation effects. Their coverage of effects is shown in Figure 4.2. It can be seen that they examined the impact of four broad categories of price presentation factors on consumers' perceived price savings from purchasing on price promotions (see Zeithaml, 1982; Dickson and Sawyer, 1990).

The first set of factors is situational. These factors encompass the overall situation for the price promotion, e.g., is the evaluation for a national brand or a private label brand, is it within a discount store or a specialty store, are consumers comparing prices within or between stores, and/or is this kind of promotion distinct (versus competition) and/or consistent (over time) or not? The second set of factors, presentation effects, addresses whether it matters how the promotions are communicated, and are some ways of doing

[1] This part of the chapter is based upon Krishna et al. (2002).



Note: See Table 4.1 for a discussion of the variables.

Figure 4.2 Variables in meta-analysis done by Krishna et al. (2002)

so better than others? For instance, is a tensile claim of 'save up to 70%' better than a claim of 'save 40%'? The third set of factors is the deal characteristics, e.g. how much of a discount is offered to the consumers. The final set of factors relates to the specific studies used in this research and attempts to control for any idiosyncratic effects from a study.

The conceptual model in Figure 4.2 posits that the above four factors may also interact in their effect on the perceived savings. For instance, the type of brand (national or local) may interact with the size of the deal to influence consumers' perceptions of the savings. According to Zeithaml's (1982) conceptual schema, the consumer acquires and encodes the 'objective price' (stimulus) to form the 'subjective price'. In Figure 4.1, the objective price is represented by the 'deal characteristics' and the 'subjective price' by 'perceived savings'. For the meta-analysis, 'perceived savings' was the dependent variable, and 'deal characteristics, situation, price presentation' and 'study effect' were the independent variables.

Data, models and results

Krishna et al. (2002) use published literature where 'perceived savings' was the dependent variable. Further, they required that deal evaluation be actually measured as opposed to inferred. Hence the focus is on experimental and not on scanner-based research (these are considered in Section 3). The ABI Inform and Psychlit indices from 1980 until 1999 were used to search for articles. In addition, they searched through *Journal of Marketing*, *Journal of Marketing Research* and *Journal of Consumer Research*, *American Marketing Association* proceedings and *Association of Consumer Research* proceedings that had been published before December 1999. Twenty articles passed their screening criteria (see Table 4.2). If an author conducted a 2 X 2 experiment, they treat this as four observations. Across all 20 articles, they have 345 observations, i.e. data points.

Across the articles, authors used different measures of 'perceived savings'. To make the different scales comparable, Krishna et al. transformed them to a percentage. Definitions of independent variables and the values of categorical independent variables appear in Table 4.1. The categorical independent variables are coded using dummy variables.

We elaborate on one typical study included in the meta-analysis. Berkowitz and Walton (1980), for instance, asked subjects to evaluate three newspaper advertisements taken from local papers. Subjects were assigned to one of four semantic (price presentation) cues – 'compare at $1.25, now $1.00', 'regular $1.25, sale $1.00', 'total value $1.25, sale $1.00', '20% off, now only $1.00'. Subjects then rated the item in the advertisement on various seven-point scales, e.g. perceived savings, willingness to buy.

Krishna et al. (2002) estimated various models on the data, e.g. a main effects model with all (45) main effects of the design variables plus the study average of 'perceived savings' (to account for idiosyncrasies of each study), and a model with all main effects plus significant interactions. At the aggregate level, all models explained more than 70 percent of the variance. Here we present the major findings from their analysis (detailed results can be obtained from their paper). Table 4.2 summarizes these findings.

- The most important factors influencing consumers' perception of the deal are the deal characteristics and price presentation effects – factors that the manager has the most control over.

Table 4.1 Independent variables

Independent variables and variable levels[a]	Definition	Articles with variance across independent variables[b]
DEAL CHARACTERISTICS		
% of deal[c]		Most studies
Amount of deal		Most studies
Additional savings on bundle		Low and Lichtenstein (1993); Yadav and Monroe (1993); Das (1992)
Base price of item		Between-article variation[d]
No. of items on deal/ no. of deals observed	Number of observations provided to subjects	Between-article variation
Size of the bundle	Number of items in the bundle presented to the subjects	Low and Lichtenstein (1993); Buyukkurt (1986)
Variance of deals	How deal amount varies over time/ uncertainty in deal price	Buyukkurt (1986)
High		
None/low		
Free gift value		
Low	• Value of free gift is small relative to base price of product	Low and Lichtenstein (1993)
High or none	• High if there is a free gift and none if there is no free gift	
SITUATION VARIABLES		
Brand type		
Fictitious		Blair and Landon (1981)
Generic		Dodds et al. (1991)
National		Berkowitz and Walton (1980)
Private		Bearden et al. (1984)
None specified		
Store type		
Department		Dodds et al. (1991)
Discount		Berkowitz and Walton (1980)
Specialty		Buyukkurt (1986)
Supermarket		
None specified		
Type of good		
Packaged		Berkowitz and Walton (1980)
Other	• Durable or soft good	Das (1992)
Category experience		
High	High versus low consumer knowledge/experience with the category	Some between-article variation
Low		
Not specified		

Table 4.1 (continued)

Independent variables and variable levels[a]	Definition	Articles with variance across independent variables[b]
Ad frame		
Advertisement	Catalogue format versus advertisement format versus shopping simulation	Blair and Landon (1981) Grewal et al. (1996) (lots of between-study variance)
Catalogue		
Shopping		
PRICE PRESENTATION VARIABLES		
External reference price		
Manufacture suggested price (MSP)		Blair and Landon (1981); Urbany et al. 1988)
Regular price		Burton et al. (1993); Das (1992)
None		Bearden et al. (1984); Berkowitz and Walton (1980) Della Bitta et al. (1981)
Objective (non-tensile) deal frame		
Coupon	• Deal given as a coupon	Berkowitz andWalton (1980); Della Bitta et al. (1981)
Dollar	• e.g. $__ off	Biswas and Burton (1993, 1994); Burton et al. (1993)
Free gift	• e.g. a free premium	Low and Lichtenstein (1993); Das (1992)
%	• e.g. __% off	Bearden et al. (1984); Chen et al. (1998)
X-For	• e.g. 2 for the price of 1	
None (final price given)		
Tensile deal frame		
Maximum	• Save up to __	Biswas and Burton (1993, 1994)
Minimum	• Save __ and more	Mobley et al. (1988)
Range	• Save __ to __	
Non-tensile (objective) deal frame	• No tensile deal frame	
Plausibility		
Implausible		Lichtenstein and Bearden (1989); Urbany et al. (1988)
Plausible – small		Grewal et al. (1996); Suter and Burton (1996)
Plausible – large		Dodds et al. (1991); Berkowitz and Walton (1980)
Plausible		Low and Lichtenstein (1993); Lichtenstein et al. (1991)

Table 4.1 (continued)

Independent variables and variable levels[a]	Definition	Articles with variance across independent variables[b]
Store frame		
Between stores	• e.g. our price, compare with _ at __	Urbany et al. (1988); Grewal et al. (1996)
Within store	• e.g. regular price __, sale price __	Berkowitz and Walton (1980); Burton et al. (1993)
Both		Lichtenstein et al. (1991)
Consistency		
High	• Of deals over time	Lichtenstein and Bearden (1989)
Low	Three articles specifically discuss manipulating 'consistency'. Lichtenstein and Bearden (1989) manipulate high and low consistency through high and low deal frequency. Burton et al. (1993) and Lichtenstein et al. (1991) depict high consistency by using a within-store frame (was $__, now only $__)	Burton et al. (1993) Lichtenstein et al. (1991)
Neither (not applicable)		
Distinctiveness		
High	• Of deal versus other brands	Lichtenstein and Bearden (1989)
Low	Three articles specifically discuss manipulating 'distinctiveness'. Of these three, Burton et al. (1993) and Lichtenstein et al. (1991) manipulate high distinctiveness through a between-store frame (seen elsewhere for $__, our price $__)	Burton et al. (1993) Lichtenstein et al. (1991)
Neither (not applicable)		
Sale announced?		
Yes	• Offered price is termed a sale	Yadav and Monroe (1993)
No	• Offered price does not state that it is a sale	Burton et al. (1993)
Free gift value		
Low	• Value of free gift is small relative to base price of product	Low and Lichtenstein (1993)
High or none	• High if there is a free gift and none if there is no free gift	
Bundle frame		
Loss		Kaicker et al. (1995)

Table 4.1 (continued)

Independent variables and variable levels[a]	Definition	Articles with variance across independent variables[b]
Mixed (gain and loss)		
Gain		
Combined prices?		
Yes	Single price for bundle	Kaicker et al. (1995);
No	Each item has its own price	Some between-study variation
STUDY EFFECT		
Number of variables manipulated		Between-article variation only
Number of subjects in cell		Within- and between-article variation
Study average		Between-article variation only
Multiple scales for DV		
Yes	• DV is measured as a sum of multiple-scale items	Between-article variation only
No	• DV is measured as a single-scale item	

Notes:
[a] Default level is given in italics.
[b] Some independent variables had variation across articles and some had variation both across and within articles.
[c] Variable is continuous.
[d] Variation in the independent variable occurred across articles, not within the same article.
[e] Variance of deals is coded with dummy variables with none/low as the base case.

- Within deal characteristics, the most important factors are the additional savings on a bundle and the deal percentage. However, as the size of the bundle increases, consumers perceive the deal less favorably. Thus small bundles with high percentage discounts are most significant for consumers.
- Within price presentation effects, Krishna et al. (2002) found several interesting interactions. First, the plausibility of the deal (or size of the deal) interacts with whether or not regular price is given. 'Implausibility' of a deal makes it less attractive. However, a large deal amount more than compensates for its lower plausibility, so that larger deals are evaluated more favorably than smaller deals. A second interesting interaction is that within-store frames (e.g. regular price $1.99, sale price $1.59) are more effective when the consumer is shopping, but between-store frames (e.g. our price $1.59, compare with $1.59 at Krogers) are more effective when communicating with consumers at home.
- Within situational effects, the most important factors are brand (both store and item). Deals on national brands are evaluated more favorably than those on private brands and generics; and consumers value deals less in stores that have higher deal frequency (discount stores) compared to stores perceived to have lower deal frequency (e.g. specialty stores).

Table 4.2 Important findings from the meta-analysis

Variables studied	Effect on dependent variables
Deal characteristics	
Amount of deal, % of deal	Both positively influence perceived saving
Variance of deals	High deal variances lead to lower perceived savings
Situational effects	
Brand type: national brands versus private brands and generics	Deals on national brands yield higher perceived savings
Type of good: packaged goods versus other (durable, soft) goods	Deals on packaged goods yield higher perceived savings
Store type: discount store versus department and specialty stores	Deals in discount stores lead to lower perceived savings
Price presentation effects	
External reference price: regular price	Presence of regular price increases perceived savings
Minimum tensile claim versus non-tensile claim	Minimum tensile claims yield lower perceived savings
Plausibility: small and plausible deals versus large but plausible deals and implausible deals	Small and plausible deals yield higher perceived savings
Consistency	Less consistent deals yield higher perceived savings
Distinctiveness	More distinctive deals yield higher perceived savings
Interactions[a]	
Regular price and deal percentage	Presenting a regular price as an external reference price reduces perceived saving when the deal percentage is extremely large
Regular price and plausibility	The presence of a regular price enhances the perceived savings of large but plausible deals and implausible deals but not small plausible deals
MSP and brand type	Presenting MSP increases perceived savings more for national brands than for other brands
Brand type and plausibility	Large but plausible deal on a national brand results in higher perceived savings as opposed to a large plausible deal on other brands
Deal percentage and store type	Large deals in department store yield higher perceived savings than those in discount, specialty stores, or supermarkets

Note: [a] The effects of interactions are explained considering the interaction effect and both the main effects.

The meta-analysis shows that many price features, other than the intrinsic price, significantly influence perceived savings and hence should be taken into account by managers in structuring deals. Another synthesis of reference pricing research has been done by Biswas et al. (1993). In addition to a narrative review, their article presents a meta-analysis based on 113 observations from 12 studies. A major difference between this earlier study and Krishna et al.'s (2002) is that the former study concentrates on statistical significance and variance explained, whereas the latter focuses on the magnitude of the effects. Second, the former study analyzes one variable at a time, whereas the latter analyzes data in a multivariate fashion. A second important reference is an integrative review of comparative advertising studies done by Compeau and Grewal (1998). This review builds upon the meta-analysis done by Biswas et al. (1993) and has 38 studies. This analysis also focuses on statistical significance and variance explained, and does so one variable at a time.

We now turn to a discussion of 'scanner data'-based research that incorporates consumers' internal reference prices.

3. Prediction models incorporating consumer reference prices

As will be clear from this *Handbook*, much research in marketing has focused on predicting consumer choice. These models typically do not use experimental data (and, as such, do not fall within the purview of our meta-analysis), but use scanner data, secondary data on consumer purchases over time. Starting with Winer's (1986) work, some choice models have tried to incorporate the notion of an 'internal reference price' – we call this body of research 'reference price effects in choice models'. Internal reference prices are constructed by consumers themselves and are 'an internal standard against which observed prices are compared' (Kalyanaram and Winer, 1995). They are used to gauge how 'good or fair' the observed price is. Conceptually, they can be construed as a 'fair price' or an 'expected price'. Note that the internal reference price is different from an 'external reference price' provided by the retailer; an external reference price is provided along with a (lower) price the retailer is offering and is used as a means to encourage consumers to purchase the product (or service). The external reference price can be, for example, a manufacturer-suggested retailer price, what the price was, what other retailers are charging, etc.

Operationally, internal reference prices have taken many forms, so that they can be based on current prices (e.g. current price of the last brand purchased), past prices (e.g. the brand's price on the last purchase occasion), or on past prices and other variables (such as market share of the brand). Briesch et al. (1997) offer a comparative analysis of reference price models that use different operationalizations of reference price – they find that models based on past prices do best in terms of fit and prediction.

Reference-price choice models are constructed so that, if the observed price is lower than the reference price, then choice probability increases; if the observed price is higher, then the choice probability decreases. While Winer (1986) incorporated a reference price effect, Lattin and Bucklin (1989) introduced a reference promotion effect so that there is a reference level of promotion frequency which dictates how the consumer responds to a promotion. Kalyanaram and Little (1994) estimate a latitude of acceptance around the reference price, and show that it is wider for consumers with higher average reference price, lower purchase frequency, and higher average brand loyalty.

Some researchers have taken the notion of reference prices one step further and have

built the concepts of prospect theory on top of reference price effects, since they lend themselves quite easily to such interpretation. A lower observed price versus the 'reference price' is seen as a 'gain' whereas a higher observed price is seen as a 'loss'. Further, 'gains' and 'losses' are predicted to have different effects on choice. According to prospect theory, 'losses loom larger than gains', i.e. losses have stronger effects compared to equivalent gains. This is tested within the context of brand-choice models by Kalwani et al. (1990) and Hardie et al. (1993), and both brand-choice and purchase and quantity models by Krishnamurthi et al. (1992). Different parameters are estimated for the effect of 'gains' versus 'losses' on choice. Most researchers find significant and predicted effects for gains and losses (losses have larger negative than gains have positive effects). Krishnamurthi et al. (1992) also show that sensitivity to gains and losses is a function of loyalty toward the brand for both choice and quantity models, and is also a function of household stock-outs for quantity models. Hardie et al. (1993) also introduce the notion of a reference brand, so that the current price of any brand is compared to the current price of the referent brand. While the aforementioned articles focus on empirical estimation, Putler (1992) incorporates the effects of reference price into the traditional theory of consumer choice and then tests it on egg sales data. Like other researchers, he too finds asymmetry for egg price increases versus decreases.

For more detailed and excellent summaries of research on reference price effects, the reader should consult Kalyanaram and Winer (1995) and Mazumdar et al. (2005).

4. Future research

This chapter shows that the price of a product can affect observed consumer behavior in various ways other than through the actual price. Both subjective price and price fairness affect consumer choice of product, purchase quantity and purchase timing. Subjective price is affected by price presentation and internal reference price, which are each composed of a host of factors, and also by '99 cent' endings, partitioned prices and temporal pricing. Similarly, perceived price unfairness has several antecedents.

We focus on price presentation effects and summarize a meta-analysis of 20 published articles in marketing that focus on price presentation. We also provide a summary of the effect of internal reference price (formed as a function of observing different prices over time) on consumer behavior.

In terms of predictive models, besides price presentation effects, there is much scope for incorporating other behavioral effects – internal reference price is just one single behavioral pricing aspect. Thus an important direction for future research is to see how price presentations affect 'consumer behavior' as opposed to 'consumer perceptions'. The studies in the meta-analysis were based upon laboratory experiments. Few studies have assessed the effect of different price presentations on consumer behavior (for an exception, see Dhar and Dutta, 1997). Of course, a major reason for this is lack of data. While scanner data record a host of information, price presentation is still not included in the data. Future research should try to obtain these additional data within the context of scanner data, and replicate the laboratory-experiment results in the field. Additionally, future research should incorporate other behavioral aspects, besides internal reference prices and price presentation effects, within predictive models.

While normative models have begun to incorporate the effects of perceived price fairness (e.g. Feinberg et al., 2002), predictive models have still not followed suit and this is

another area for future research. Yet another area fruitful for research is the behavioral aspects of online shopping, e.g. how shopping bots may have altered price response behaviors online as well as influenced responses in physical stores. Researchers could also further examine the lower relevance of price when the product is linked to a 'cause' (e.g. part of proceeds from the sales of the product go towards AIDS research). Arora and Henderson (2007) show that these 'embedded premiums' are in a sense a price deal not to the consumer but to the cause. This needs additional work. Besides brand choice, purchase quantity and timing, another construct to focus on is consumption and how perceived price affects it. Clearly, there is much left to study in the area of behavioral pricing.

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5 Consumer search and pricing

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Abstract

In most cases, consumers must search for information about prices and product attributes, and find it too costly to become perfectly informed. The consequent departure from perfect information affects the pricing behavior of sellers in a variety of ways. The purpose of this chapter is to review the literature on consumer search, and on the consequences of consumer search behavior for the behavior of markets. The review first focuses on summarizing theoretical models optimal search, and on how costly search may affect the behavior of markets. Two of the key results in this literature are that price dispersion should exist in equilibrium, and that differences in search costs provide a motive for price discrimination. After summarizing the theoretical models, the review presents empirical results on consumer search, and on pricing by sellers given differences in consumer search costs. Specific results for different information sources, including word of mouth, advertising, retailing and the Internet are discussed.

Introduction

In his seminal paper Stigler (1961) pointed out that there appears to be substantial and persistent price dispersion in markets for commodities such as coal. This is a direct contradiction of the standard model of perfect competition, in which the law of one price should prevail. Setting out to explain this anomaly, Stigler pointed out that the standard assumption that consumers are informed about all alternatives should be violated if search is costly. Since it only pays to search up to the point where the marginal benefits of search equal its marginal costs, a rational consumer will accept a price above the minimum when the expected gain from searching further is less than the cost. Therefore rational consumers can pay a price higher than the minimum, and price dispersion can result.

Thus began the study of the relationship between consumer search and market prices, which has burgeoned into a large and diverse literature over the past 40+ years. The objective of this review is to summarize this literature. Since the initial literature, including Stigler's article, was focused on the consumer side of the market, I shall consider models of optimal consumer search first. Then I shall discuss equilibrium models of search and price dispersion, and the empirical literatures on pricing and search that are related to these models. Finally I shall consider research that explores the relationship between search, pricing and different institutions that provide information and facilitate sales. My intent is to provide a broad overview of these very diverse areas that shows how they fit together rather than to provide a detailed review of each that cites all of the available references.

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Models of consumer search

Stigler (1961) considered a decision rule in which the searcher sets the number of items to be searched as the number at which the expected gains from an additional search are equal to the expected cost of that search. In this model all alternatives are assumed to be equally promising *a priori*, and search for an item is assumed to yield a complete understanding of that item. While this is sufficient to prove the point that expected-utility-maximizing consumers with positive search costs should not be fully informed, Stigler's formulation is a very simplified model of search that does not capture the more general case in which priors on alternatives may be different, and search may be sequential. Nevertheless Stigler's model may be a reasonable approximation to search in some situations; for example when soliciting bids for repair work when the bidder has time to prepare a proposal, and the purchase is not made until proposals are received. In this case, if one knew the variance of payoffs prior to searching, and the costs of soliciting and evaluating each contractor's proposal, tables in Stigler's article or in David (1970) and Ratchford (1980) could be used to determine the number of contractors to solicit bids from.

While still restrictive in many respects, the model of Weitzman (1979) considers the more general case in which the consumer may have different priors across alternatives, and in which the consumer can search sequentially. Weitzman assumes expected utility maximization, that search for an item uncovers all information about it, that there is recall, that there is no parallel search, and that there are no joint costs of search in which several alternatives can be inspected for the price of one. Given these assumptions, Weitzman proves the optimality of a stopping rule in which alternatives are searched in order of their reservation utility, and the consumer stops searching if the payoff exceeds the reservation utility of the next best alternative. Otherwise the consumer searches the alternative that is next in the ranking, and repeats the process until an alternative that meets the stopping criterion is found.

The reservation utility for alternative i, V_i^R, is the payoff value at which the consumer would be indifferent between searching the item at a cost of C_i or accepting the payoff V_i^R. The value of V_i^R is the one that equates the cost of searching i with the expected gain from looking for a payoff that exceeds V_i^R:

$$C_i = \int_{V^R_i}^{\infty} (V_i - V_i^R) f(V_i)\, dV_i$$

If the consumer already has an item with a payoff greater than V_i^R, he/she should stop since the expected gain from search is less that the cost. If the consumer does not have a payoff as high as V_i^R, he/she should continue to search because the expected gain will exceed the expected cost.

As an example, consider the case where V_i is normally distributed, with a mean $\overline{V}_i$, standard deviation σ_{V_i}. Then the integral on the right becomes σ_{V_i} times the value of the unit loss integral L_i^R that equates the right side with C_i:

$$C_i = \int_{V^R_i}^{\infty} (V_i - V_i^R) f(V_i)\, dV_i = \sigma_{V_i} L_i^R$$

The reservation value of i can then be calculated as

$$V_i^R = \overline{V}_i + \sigma_{V_i} z_i^R$$

Table 5.1 Example of application of the Weitzman model

Rank	c	σ_{vi}	$L^R = c/\sigma_{vi}$	z^R	$\overline{V}_i$	$V_i^R = \overline{V}_i + \sigma_{vi} z_i^R$	$\Pr(V_i > V_{i+1}^R)$
1	3	15	0.20	0.49	50	57.35	0.3156
2	3	10	0.30	0.22	55	57.20	0.6179
3	6	20	0.30	0.22	50	52.02	

Consider the example in Table 5.1. The reservation utilities V_i^R are seen to depend on the costs of search, standard deviation of utilities and expected utility. Although the second alternative has the highest expected utility, the first has a larger standard deviation, which leads it to have the highest reservation utility. Basically the first alternative offers a better chance of 'striking it rich'. The third alternative gets set back in the order of reservation utilities because it has a high search cost (6). Weitzman's rule dictates that consumers should search the ranked first alternative first, with a probability of being able to stop after one search of 0.3156. If the payoff from the first search is less than 57.2, the reservation utility of the second alternative, the consumer should continue searching. Similarly, if the payoffs from both the first and second searches are less than 52.02 the consumer should go on to the third alternative. At this point the consumer should choose the best of the three items. The expected number of searches = 1*(0.3156) + 2*(1 − 0.3156)*(0.6179) + 3*(1 − 0.3156)*(1 − 0.6179) = 1.95

Moorthy et al. (1997) applied the Weitzman model to develop an explanation of the relationship between prior brand perceptions and search. In their model, prior brand perceptions govern search, and these are expected to vary with experience. In particular, they show that prior brand perceptions can create the U-shaped relationship between knowledge and search that is often uncovered in laboratory experiments (Johnson and Russo, 1984). They tested their hypotheses on a panel of automobile shoppers in which data were obtained as the search progressed. They found that priors and search effort, and brands and attributes searched, vary with experience as hypothesized.

Around the time of Weitzman's article, labor economists began using hazard models to model search for a job and the duration of unemployment; good examples of these models are Lancaster (1985), Wolpin (1987), Jones (1988) and Eckstein and Wolpin (1990, 1995). Since there is a direct analogy between searching for the highest wage for a job and for the lowest price for a product, and since the structure of the search problem is similar in both cases, these job search models can also be applied to consumer price search with only minor modifications.

An application drawn from the labor economics literature to modeling the duration of search for automobiles was presented by Ratchford and Srinivasan (1993). In their model, price offers arrive at a constant rate, with the distribution of price offers following a Pareto distribution. The hazard of terminating the search and buying a car is then the product of the arrival rate of offers and the probability that an offer exceeds the reservation price. The observed outcomes of prices paid and time devoted to search result from two equations: an equation that determines the level and rate of arrival of offers, which depends on seller characteristics and the consumer's efficiency at search; and an equation that determines the reservation price, which depends on the same factors plus the cost of

search per unit of time. Ratchford and Srinivasan (1993) employ these equations in estimating the determinants of observed prices and search time, and in calculating monetary returns to additional search time.

The job search models of Wolpin (1987) and Eckstein and Wolpin (1990) are early examples of dynamic structural models. Their structural modeling approach has carried over into the literature on packaged goods choice in the form of models that postulate Bayesian learning of brand attributes through consumption (Erdem and Keane, 1996; Erdem et al., 2003; Mehta et al., 2003).

This structural approach has recently been applied to consumer search prior to purchase by Erdem et al. (2005). Using a very rich panel dataset that tracks a sample of potential computer buyers from early in their search to purchase, the authors simultaneously model gathering information from retailers, and the final choice of a computer. The panel has six waves in which respondents report the sources that they consulted, their quality perceptions of the competing brands, their price expectations, and, if applicable, their choice. Respondents are assumed to follow a Bayesian updating process for incorporating quality information from five information sources. Specifically, if L_{ikt} is a dummy variable indicating whether consumer i visits information source k at time t, if x_{ijkt} is a similarly defined noisy but unbiased signal from a given source, z_{ijt} is consumer i's quality perception error at t, and σ^2_{ijt} is the variance of perceptions at time t, the Bayesian updating formula for quality perceptions is given by (Erdem et al., 2005, p. 219):

$$\sigma^2_{ijt} = \left[\frac{1}{\sigma^2_{j0}} + \sum_{s=1}^{t}\sum_{k=1}^{5}\frac{L_{iks}}{\sigma^2_k}\right]^{-1}$$

$$z_{ijt} = z_{ijt-1} + \sum_{k+1}^{5} L_{iks}\frac{\sigma^2_{ijt-1}}{\sigma^2_{ijt-1} + \sigma^2_k}(x_{ijt} - z_{ijt-1})$$

where σ^2_{j0} is the variance of prior information, σ^2_k is a measure of the reliability of source k, and information signals are assumed to be independent across sources. Smaller values of σ^2_k lead to smaller σ^2_{ijt} and more complete updating.

Given the above Bayesian updating mechanism for information sources, and an adaptive model of price expectations, Erdem et al. estimate a structural model in which each consumer optimizes the choice of the five information sources over the six periods of the panel, optimizes the timing of the choice given price expectations, and optimizes the make and quality level of computer chosen. While this model assumes that consumers can make very complex calculations, it also represents a direct empirical application of an optimizing model of search. Since this paper represents the state of the art in combining theoretical and empirical analysis of consumer search, it deserves careful study.

Models of search and pricing

If many consumers do not search much, there is a potential opportunity to exploit their ignorance by charging higher prices, so that price levels should be inversely related to search. Conversely, while some consumers may not search, those who can afford to search extensively will attempt to locate lower prices. This leads to the possibility that price dispersion, which is commonly observed in actual markets, will exist in equilibrium.

For our purposes, price dispersion may be defined as offering physically identical items for sale at different prices. Price dispersion may be either spatial (across sellers at one

point in time), or temporal (prices vary within a seller over time). There are at least four explanations for equilibrium price dispersion in the literature:

- Price dispersion due to differences in search costs and seller costs (Carlson and McAfee, 1983).
- Periodic sales due to adoption of mixed strategies by competing sellers to capture sales from high and low search cost segments (Varian, 1980).
- Markdowns due to demand uncertainty (Lazear, 1986; Pashigian, 1988; Smith and Achabal, 1998).
- Differences in services provided by sellers (Ehrlich and Fisher, 1982; Ratchford and Stoops, 1988, 1992).

Each of these explanations is discussed below.

While earlier equilibrium models of price dispersion had been developed (e.g. Salop and Stiglitz, 1977), Carlson and McAfee (1983) presented a model that was amenable to empirical testing, and was later tested by Dahlby and West (1986). The model of Carlson and McAfee addresses a homogeneous commodity sold by different sellers. Each buyer in the market will buy one unit. *A priori*, consumers know the distribution of prices, but not the specific price of any item. They search sequentially for the lowest price using a stopping rule in which search is terminated when the expected gain from additional search is less than the constant cost of the additional search. This cost per item searched is assumed to vary across consumers with a uniform distribution bounded at 0 on the low end. In this framework, a consumer with the highest search cost still has a $1/n$ (n = number of items) chance of getting any price, including the lowest one. A consumer with a search cost low enough to justify searching further if the highest price is encountered has a $1/(n - 1)$ chance of getting any of the other prices, and so on. Given the uniform distribution of search costs, Carlson and McAfee derive a demand function of the following form:

$$(q_j/\bar{q}) = 1 - (1/T)(p_j - \bar{p})$$

where j refers to firm, 'bar' denotes mean, q is quantity, p is price, and T is the upper bound of the uniform distribution of search costs. Increases in T (upward shifts in the distribution of search costs) make demand less sensitive to price changes.

On the supply side, Carlson and McAfee assume that unit costs differ across firms by a parameter α_j. Given the demand curve outlined above, their assumed cost function, and n competing sellers, they derive Nash equilibrium prices for each seller. Given that firms earn nonnegative profits, they show that the variance of prices in this model is proportional to the variance in the unit cost parameters α_j. If this variance is 0 and all firms have the same cost function, there will be no price dispersion: price dispersion is driven entirely by differences in unit costs in this model. However, if costs are the same for all firms, each firm will charge an equilibrium markup that is proportional to T, the highest search cost. Thus search costs affect price levels, and the variation in costs drives price dispersion.

While the Carlson and McAfee model leads to demand and cost functions that can be estimated empirically, it does not readily extend to differentiated products. Given the potential for empirical application, efforts to make this model applicable to products with different attributes may be worthwhile.

Salop and Stiglitz (1977) considered a monopolistically competitive market in which there were two segments of consumers – completely informed and completely uninformed, and showed that two prices could emerge in the market even though the competing sellers have identical U-shaped cost curves. As noted by Varian (1980), this a model of spatial competition.

A weakness of this model is that consumers never learn about the existence of the lower prices. To address this problem, Varian (1980) formulated a model of temporal price discrimination in the face of segments of informed and uninformed consumers, and a market with identical firm cost functions and free entry. Since firms are torn between the desire to extract surplus from the uninformed consumers and the desire to capture all of the business of the informed consumers by charging the lowest price, there is no pure strategy equilibrium in this model. The Nash equilibrium solution that maximizes expected profit for each firm is to select prices at random from an equilibrium distribution function. This allows each firm to capture a surplus from the uninformed consumers, while occasionally having the lowest price and therefore getting the business of the informed consumers. One way to interpret the practice of randomly offering relatively low prices in an effort to capture the informed consumers is that these low offers represent sales or promotions. Thus Varian's analysis provides a rationale for sales and promotions as the outcome of mixed strategies in a competitive market when there are differences in the degree to which consumers are informed. In the Varian model, price dispersion exists over time even though firms have identical costs. A testable outcome of the model is that the rank order of prices charged by firms in a market should fluctuate randomly over time.

The mixed strategy model has become a staple of models that explain price dispersion, promotions, advertising and other phenomena. For example, although he uses the terminology 'loyals' and 'switchers' instead of 'uninformed' and 'informed', Narasimhan (1988) employs a mixed strategy model similar in structure to Varian's to study the frequency and depth of promotions. Another example is Iyer and Pazgal (2003), who present a mixed strategy model that explains the dispersion of posted prices at Internet shopping agents. Recently, Baye and Morgan (2004) have shown that a mixed strategy model, and dispersion of offer prices, can be generated if firms depart from maximizing behavior, even if all consumers have zero search costs.

While the mixed strategy model based on segments with different amounts of information or brand loyalty provides one explanation for the existence of periodic promotions and sales, an alternative explanation is based on seller efforts to determine what consumers will pay for an item. The basic idea is that sellers who are uncertain about demand may initially charge a high price to see if any customers will pay it. Failure to sell the item at that price conveys to the seller that the distribution of consumer willingness to pay must lie below it. It becomes optimal to reduce the price. Failure to sell at the lower price conveys information that the distribution of willingness to pay lies below the reduced price, triggering a further price cut, and so on. This approach is feasible for goods like fashion merchandise because the consumer knows that inventories of the item will not be replenished once it sells, which makes it risky to wait for prices to be reduced further. A complete model of clearance sales is provided by Lazear (1986), and empirical studies based on this model are provided in Pashigian (1988), Pashigian and Bowen (1991) and Pashigian et al. (1995). A decision support system for optimal clearance pricing was developed by Smith and Achabal (1998).

A final potential determinant of price dispersion that is unrelated to differences in physical product characteristics is differences in advertising or other services provided by sellers. The basic idea, first developed by Ehrlich and Fisher (1982), is that advertising and other services are valued by consumers because they cut down on search costs, and that consumers will therefore willingly pay a higher price for goods that are bundled with the services. If the marginal costs of providing the services are non-decreasing in both amount per customer and number of customers, optimal trade between customer i and firm j can be expressed (Ehrlich and Fisher, 1982) as

$$-\,dL_i/dS_j = dp_j/dS_j = dC_j/dS_j$$

This implies that the marginal reduction in search costs (L) of consumer i due to advertising or other services provided by firm j ($-\,dL_i/dS_j$) is equal to the marginal increase in price that firm j can command on the market resulting from a marginal increase in services (dp_j/dS_j), which in turn is equal to the marginal cost to firm j of supplying the services (dC_j/dS_j). If the above assumptions about the marginal costs of services are satisfied, and there is free entry, an equilibrium with consumers choosing service levels that satisfy the above conditions, and prices equal to average cost including the cost of providing the services ($p_j = AC_j$) will result. Thus differences in observed prices across sellers result from differences in advertising or other services provided by firms. In turn these differences result from differences in consumer demand for the services.

Thus we have four potential explanations for price dispersion in markets. Spatial price dispersion may be related to differences in search costs between buyers coupled with cost differences between sellers, and to differences in use of advertising and other services provided by sellers. Both spatial and temporal price dispersion may be related to differences in search costs and mixed strategies over time, and temporal price dispersion may be related to reducing prices over time in response to information about willingness to pay. Aside from these explanations of price dispersion, there is a consistent finding that increases in the mass of consumers with high search costs will lead to higher prices and possibly to a higher supply of services that reduce search costs.

Empirical evidence on price dispersion and search

We shall first discuss the extensive empirical literature that tests various hypotheses about price dispersion suggested by the models of price dispersion outlined in the preceding section. Since the results of these models depend on consumer behavior, we shall also examine evidence in the literature on consumer search that is related to the empirical results about price dispersion and its antecedents.

Price dispersion

The dispersion of offer prices of physically identical items in retail markets has been consistently found to be quite large, even for relatively expensive items. For example, Sorenson (2000) found an average coefficient of variation of prices of prescription drugs across retailers in a particular market to be 22 percent. Dahlby and West (1986) found a coefficient of variation of auto insurance prices across insurers in a particular market of between 7 and 18 percent. In their study of 39 products in the Boston market, Pratt et al. (1979) found coefficients of variation ranging across products from 4.38 percent to 71.35

percent, with a mean of 21.6 percent across the 29 items. In their study of prices posted at Biz Rate, Pan et al. (2002) found average coefficients of variation across eight broad categories of between 8.3 and 15.4 percent. Although these measures of dispersion do decline somewhat with price levels (Pan et al., 2006), they are still substantial for high-ticket items.

The existing evidence indicates that most of the variation in prices across retailers cannot be explained by differences in retail services, at least with existing measures of services. Pan et al. (2002) found that between 5 and 43 percent of the variation in prices of homogeneous items across the eight categories studied could be explained by differences in services across sellers, and that this percentage of explained variation was under 25 percent for seven of the eight categories. Across different products in a category, evidence in the extensive literature on price–quality relations also indicates that differences in prices across items are not closely related to differences in their quality. This literature consistently indicates that the correlation between price and overall quality is low (e.g. Tellis and Wernerfelt, 1987), or that many brands have a price that is well above a frontier that defines the minimum price for a given quality or set of attributes (Maynes, 1976; Kamakura et al., 1988).

Although uncontrolled differences in service or product attributes may be part of the explanation for observed price dispersion and low price–quality correlations, the existing evidence seems more consistent with costly search. For example, Sorenson (2000) found that prices for repeatedly purchased prescription drugs had lower margins and less dispersion than less frequently purchased ones. Because the annual expenditure is higher, incentives to search for drugs are greater, and Sorenson's evidence is therefore consistent with consumer incentives to search for lower prices. Sorenson also concluded that at most one-third of the observed price dispersion can be attributed to pharmacy fixed effects, which may be due to some combination of cost and service level differences across pharmacies.

Dahlby and West (1986) employed the model of Carlson and McAfee (1983) in their study of price dispersion in an automobile insurance market, and concluded that price dispersion in this market can be explained by costly consumer search. Employing a unique dataset on market shares and prices, Dahlby and West (1986) estimated distributions of search costs for buyers of auto insurance that explained the observed variation in prices and market shares.

However, data on sales and market shares of items are generally difficult to obtain for specific sellers. To remedy this problem, Hong and Shum (2006) showed that, if one assumes optimal search by consumers and pricing according to an optimal mixed strategy by each seller, the distribution of search costs can be recovered from the observed distribution of prices. The basic idea is that a given distribution of search costs implies a particular frequency distribution of prices that arise from the optimal mixed strategies. If the observed frequency distribution corresponds to the optimal one, the distribution of search costs can be recovered. Using this approach, the authors developed a non-parametric estimator of the distribution of search costs for a fixed sample size model of search, and a maximum likelihood estimator for a sequential search model, under the maintained assumption that the distribution of search costs follows a gamma distribution. The authors presented some limited empirical evidence on search costs derived from observed price distributions of four books.

Search

Articles that are representative of the literature that examines the overall extent of pre-purchase search for consumer durables are: Punj and Staelin (1983); Wilkie and Dickson (1985); Beatty and Smith (1987); Srinivasan and Ratchford (1991); Ratchford and Srinivasan (1993); Moorthy et al. (1997); Lapersonne et al. (1995). A consistent finding of this literature is that the overall extent of search is limited for many buyers, and that the number of alternatives seriously considered for purchase is typically a small fraction of the number available. Despite the limited search, Ratchford and Srinivasan (1993) estimated that consumers tend to search until they are reasonably close to the point where the marginal saving in price equals the marginal costs of search. The U-shaped relationship between knowledge and search (Moorthy et al., 1997) discussed earlier suggests that price dispersion may result partly from price discrimination against consumers with low knowledge.

A number of studies have addressed price search by grocery shoppers. Carlson and Gieseke (1983) found that the percentage saved increases with stores shopped. Urbany et al. (1996), and Putrevu and Ratchford (1997), studied the relation between self-reported grocery search activities and attitudinal and demographic variables. They found that perceived price dispersion, knowledge of prices, ability to search and access to price information are positively related to search, while measures of time costs are negatively related. Fox and Hoch (2005) studied the impact of shopping more than one store on the same day, which they defined as cherry picking, and found that the savings resulting from the additional trip averaged $14.66, which is high enough to justify the extra trip for the average consumer (the trip is justified as long as its opportunity cost is less than $14.66).

While other authors employed either panel data on actual prices, or survey data, Gauri et al. (2007) collected both types of data. They studied both spatial (more than one store in a time period) and temporal (stocking up at one store when promotions are offered) dimensions of search and found that each search strategy can generate about the same level of savings, while a combination of the two strategies can generate the highest savings. They also found that patterns of search were largely driven by consumer geographical locations relative to stores.

There is a more micro body of research that infers how consumers search for repeatedly purchased items that are sold in a supermarket. As with consumer durables, survey research indicates that consumers do not search extensively for specific grocery items. For example, Dickson and Sawyer (1990) found that only about 60 percent of consumers checked the price of the item they bought before purchase, and that less than 25 percent checked the price of any competing brand. A majority of consumers could not accurately recall prices that they paid.

Consistent with these findings, models of costly and incomplete search have been estimated on scanner panel data. Murthi and Srinivasan (1999) built a model in which consumers evaluate alternatives only part of the time, and show that this provides better predictive performance than models that do not incorporate this partial evaluation behavior. Bayesian learning models were employed by Erdem and Keane (1996), Erdem et al. (2003), and Horsky et al. (2006) to represent the evolution of consumer preferences as they gain more experience with different brands. Mehta et al. (2003) combined the extensive body of literature on consideration sets (see the references in their paper),

Bayesian updating of quality and price perceptions, and a search model that balances benefits and costs of search, to determine which brands are considered on a particular occasion.

Summary of empirical results

The extensive theoretical literature on how consumers should search indicates that they should terminate their search at the point where the expected gain from additional search is less than the expected cost. If this search is costly, consumers should not gather complete information on all alternatives, and if it is costly enough, they should not search at all. Differences in gains and costs of search across consumers should determine differences in the amount of search that they undertake.

While individual consumers may not behave optimally according to a normative decision rule, the empirical literature on search generally indicates that differences in search across consumers are consistent with the predictions of the normative models. In both durables and grocery markets, it appears that consumers who perceive more gains from search actually do search more, and that more search is associated with savings. In durables markets, there is a group of consumers, generally knowledgeable and experienced, who do not search extensively. Nevertheless, while this limited search appears to be partly due to prior information that makes further search unnecessary, and may also be due to high search costs, one wonders if there is more to the story.

Search, sources of information and pricing

While the market models of search and pricing outlined above usually abstract from specific sources of information, it is clear that consumers use a variety of sources in the course of their search. Following Klein and Ford (2003), these information sources can be broadly classified as personal (word-of-mouth, talking to salesperson, inspection at the retail outlet), and impersonal (advertising, *Consumer Reports*). They can be further classified as seller-sponsored attempts to influence sales (advertising, salesperson), and neutral or objective (friend/relative, *Consumer Reports*). Finally, the impersonal sources can be classified by medium (Internet, print). Because they involve considerations related to search and pricing that have not yet been incorporated into this review, we shall concentrate our discussion on word-of-mouth, advertising, retail and the Internet.

Word of mouth

There has been extensive study of word of mouth as a source of information in automobile purchases, with the results generally indicating that heavy users of this source tend to be young, female, inexperienced at buying cars, and low in confidence about their ability to judge them (Furse et al., 1984; Ratchford et al., 2007). They are likely to employ a purchase pal who is viewed as having more knowledge of car buying in their search (Furse et al., 1984).

The latter indicates an important consideration in studying word of mouth as an information source: someone must supply the information. This role of information supplier often appears to be filled by persons described as market mavens (Feick and Price, 1987). Market mavens are individuals who tend to collect a broad array of marketplace information with the intent of sharing it with others (Urbany et al., 1996). They appear to collect more information about food, drug, and other items sold at grocery stores (Feick

and Price, 1987; Urbany et al., 1996). The implication is that market mavens, who appear to enjoy gathering and sharing marketplace information, may play a significant role in enhancing the efficiency of consumer markets.

Advertising

Since the advertiser is normally engaging in this activity in order to make money, and consumers are likely to be aware of this, the possibility that advertising may be a signal rather than a direct source of information needs to be discussed. The possible role of advertising in cutting down on search costs has been discussed above. But there are cases in which the veracity of advertising cannot be verified through pre-purchase search (Nelson, 1974). There have been many attempts to develop formal arguments about the role of advertising and price as signals of quality in cases where consumers do not find it cost-effective to learn about quality prior to purchase (this work is reviewed by Kirmani and Rao, 2000). One of the major arguments in this literature is that advertising serves as a performance bond to motivate the firm to maintain its quality: firms advertise up front to convince consumers that they will maintain their quality; in return they get a price premium that is forfeited if their quality deteriorates. Since the firm cannot earn an adequate return on the advertising investment if it allows quality to decline, the advertising signal is credible (Klein and Leffler, 1981; Shapiro, 1983). While the rationale for the result is different from the case of informative advertising, the outcome is similar: in Ehrlich and Fisher (1982) consumers pay a higher price to avoid search costs; in signaling models they pay a higher price to get insurance of high quality.

In contrast to the signaling models discussed above, which have the most direct application to manufactured goods, Bagwell and Ramey (1994) modeled the use of advertising as a signal in retail markets. Their clear prediction is that advertising will be associated with lower prices and better buys. In their model, investments in selling technology lower costs, expansion of product line increases sales from any given set of customers, and marginal selling costs are constant or declining. All of these factors are complementary and allow the larger retailer to offer lower prices. Consumers who are aware of the heaviest advertiser employ advertising as a signal to patronize that retailer. They are rewarded with the lowest prices, while that retailer achieves the best information technology, broadest product line and lowest marginal costs. Other research related to search in retail markets is discussed in the next section.

Retailing

Since retailers not only function as an information source, but also set or negotiate prices, provide locational convenience, assemble assortments, hold inventory and finalize transactions (Betancourt, 2004), their role in the search process is unique. All of these activities have an impact on the full price of the product (price plus search and transaction costs). In general, since information, convenience, assortments, inventories and other services reduce search costs, retailers who provide them can cover their cost through higher prices. We shall review a number of studies that have addressed these tradeoffs between services that reduce search costs and price.

Messinger and Narasimhan (1997) studied the impact of large assortments that create economies of one-stop shopping. In their model, which is similar in structure to the model of Ehrlich and Fisher (1982) discussed above, the equilibrium assortment of a

supermarket is the assortment that equates the marginal saving in consumer shopping costs with the marginal cost to the store of providing a larger assortment. The cost saving to consumers comes from spreading a fixed travel cost over a higher number of items bought. The authors estimate that consumers trade a 1–2 percent increase in store margin for a 3–4 percent decrease in shopping costs that results from the large supermarket assortments.

The desire of buyers to shop in one location to minimize search costs often leads retailers of a given type to locate proximate to one another even though this creates more competition between them. For example, automobile retailers often cluster together, and major specialty stores for clothing and sporting goods tend to locate in the same mall. This clustering benefits buyers by lowering the cost of shopping for multiple items, or the cost of comparison shopping. In the latter case, it also makes the clustered retailers more competitive, which they endure because the clustered site is attractive to consumers (Wernerfelt, 1994b). A study by Arentze et al. (2005) provides a framework for the estimation of these retail agglomeration effects, and a case analysis that indicates that the effects on demand are substantial.

Once a potential buyer incurs the cost of a trip to a retailer, the retailer gains a measure of monopoly power over the buyer: if the buyer does not purchase, the cost of going to the next store must be incurred. Knowing this, the buyer will be more likely to patronize the retailer if the retailer can commit to not exploiting the buyer's sunk costs of traveling to the retailer. Wernerfelt (1994b) explains that such a commitment can be achieved by the co-location described above (the cost of going to the next seller becomes low), and also by price advertising that provides a legal commitment to provide the advertised price. Conversely, Wernerfelt (1994b) shows that retailers can employ negotiated prices to soften price competition. Manufacturers can also soften price competition between retailers by making the models available at competing retailers slightly different, thereby making it difficult for consumers to make price comparisons (Bergen et al., 1996).

One case in which the buyer's sunk travel costs may be exploited is when a stock-out is encountered. In this case, because the cost of the extra trip may not be worth it, the consumer may still buy other items from the retailer and may substitute for the item that is subject to the stock-out (see Anupindi et al., 1998 for a method for estimating substitution effects when stock-outs occur). Hess and Gerstner (1987) show that retailers may be able to induce an extra trip by using a rain check policy when there is a stock-out.

Since retail salespeople appear to be a key source of consumer information for appliances and durables (Wilkie and Dickson, 1985), it is important to examine the circumstances under which salespeople will be used as an information source. Wernerfelt (1994a) presents a model in which salespeople will be the preferred source of information for complex products in which a dialog between salesperson and consumer is needed to establish a match, and in which the salesperson is motivated to give honest answers by the prospect of repeat business.

Search and the Internet

Since the advent of the Internet provided an altogether new information source and form of retailing that quickly received widespread use by buyers and sellers, it is not surprising that this medium has been the subject of a great deal of theoretical and empirical research. The early expectation was that the Internet would reduce search costs and lead

to something approaching Bertrand competition. For example, Bakos (1997) predicted that the Internet would increase the participation of consumers in markets, and create improved matches between buyers and sellers. However, it did not take long for more sober views to emerge. The paper by Lal and Sarvary (1999) provides one important exception to the belief that the Internet will always increase competition. The authors show that, by making it easy to order over the Internet, the cost of acquiring a brand that has been bought in the past relative to an unknown brand that requires inspection before purchase is altered. One can acquire the known brand over the Internet at a low cost but must incur the cost of traveling to a retailer to get the needed information about the unknown brand. This gives the seller of the known brand a cost advantage that he/she can exploit in setting prices. Thus the Internet can promote brand loyalty and lessen competition.

Internet shopping agents (ISAs) that present comparative price data for competing sellers have become a common feature of Internet commerce. Despite the fact that users of an ISA should have no trouble determining which seller charges the lowest price, a large number of studies have shown that prices listed on ISAs typically exhibit a large degree of dispersion, similar in magnitude to 'brick and mortar' retail prices (see the review in Pan et al., 2006). Baye and Morgan (2001) and Iyer and Pazgal (2003) have explained this apparent anomaly as the adoption of mixed strategies. Firms want to trade off between extracting surplus from non-searching (loyal) customers and obtaining the business of those who consult the ISA. Similar to Varian (1980), this leads sellers who belong to the ISA to choose mixed strategies, which leads to the observed dispersion in posted prices. Because the chance of having the lowest price declines as the number of sellers increases, Iyer and Pazgal (2003) show that, as long as the reach of the ISA does not increase substantially with the number of members, ISA members will give more weight to loyal customers and charge higher prices as the number of members of the ISA increases. Since the chance of getting the business of ISA shoppers declines as the number of sellers increases, at some point it will be more profitable to cater exclusively to the non-ISA customers. Thus not all sellers will join an ISA. For the three categories they studied (books, music CDs and movie videos), Iyer and Pazgal (2003) did find evidence of variation in the identity of the seller offering the minimum price that is consistent with mixed strategies, and a tendency of prices to increase with the number of sellers.

Aside from the evidence of considerable dispersion of posted prices among Internet retailers, there is a body of evidence that indicates that the Internet does lead to lower prices and more efficient search on the part of consumers. For example, for data collected from early 1998 through early 1999, Brynjolfsson and Smith (2000) found that online book and CD prices were 9–16 percent below the offline prices of the same items. Garbarino (2006) shows that the lower online book and CD prices have persisted though 2006, although the gap has narrowed in recent years. Additional evidence that the Internet leads to lower prices is provided by Brown and Goolsbee (2002) and Zettelmeyer et al. (2006). Using micro-level data on transaction prices for term insurance that allows estimation of relationships between prices paid and differences in Internet use, Brown and Goolsbee (2002) determined that the Internet lowered term insurance prices by 8–15 percent from 1995 to 1997. Using a matched set of data on transaction prices and survey data on search behavior, Zettelmeyer et al. (2006) estimated that access to price data and referrals through the Internet leads to a decline

in transaction prices of about 1.5 percent, and that the benefits of the Internet accrue mainly to those who dislike bargaining.

As pointed out by Bakos (1997), the Internet need not lower prices if it makes it easier to locate sellers that provide a better match to consumer preferences. The better match can allow the seller to command a higher price. Lynch and Ariely (2000) found evidence of this in their experimental study of wine purchasing. More accessible quality information did lead to decreased price sensitivity in their experiments.

In addition to influencing prices, the Internet can affect other aspects of search. In particular, it may affect the total amount of effort that consumers put into their search in either direction: by allowing consumers to search more efficiently, the Internet should lead to a reduction in the effort required to obtain a given amount of information; however, the increased efficiency may make it cost-effective to attempt to locate more information than would otherwise be the case. Evidence from data on search for automobiles before and after the Internet appeared suggests that the latter effect predominates and that the Internet tends to lead to increased total search (Ratchford et al., 2003; Ratchford et al., 2007).

In addition to affecting the total amount of search, the Internet should also alter the allocation of effort between sources. Evidence for automobile search in Ratchford et al., (2003) and Ratchford et al. (2007) indicates that the Internet has had a major impact on time spent with the dealer, considerably reducing this time, and specifically reducing time spent in negotiating price with the dealer. This is consistent with the finding cited above that the Internet leads to lower prices for automobiles. Consumers do appear to come to the dealer with price information obtained from the Internet, making the price negotiation more efficient in terms of time spent, while at the same time neutralizing the salesperson's advantage in negotiating price. This should ultimately have an impact on margins that can be obtained by dealers, and on the number and skill of salespeople that they retain.

Conclusions and future research

Forty-plus years after his original article, Stigler's basic insight that search is costly, and that this will create price dispersion, still holds. Since the dispersion of offer prices for physically identical items is a pervasive phenomenon, even in cases where prices are easy to compare, models that fail to account for this may be assuming away something important and should be treated with caution.

The existing evidence about consumer search for both durables and groceries indicates that buyers stop well short of obtaining complete information, and in many cases obtain almost no new information. However, given that search is costly, it is not clear that consumers systematically search less than some normative model might tell them to. In fact, evidence presented in Ratchford and Srinivasan (1993), Fox and Hoch (2005) and Gauri et al. (2007) indicates that marginal gains to search are not far out of line with marginal costs. Moreover, empirical studies of search behavior generally indicate that search varies across consumers in ways that are consistent with fundamental search models.

One reason why it is hard to determine whether consumers search too little or too much compared to a normative model is that costs of search are difficult to measure. Time costs appear to differ considerably from wage rates, and shopping time may be a consumption good in itself (Marmorstein et al., 1992). Moreover, while there are obvious constraints

on consumers' ability to process information, this information-processing capacity generally is not incorporated into estimates of search costs. Learning more about the nature and magnitude of search costs would seem to be a potentially fruitful area for further research.

Existing models indicate that average and minimum prices, and price dispersion, increase with the variation in search costs across consumers (an assumption that the lowest search cost is 0 – some consumers are fully informed – is generally required to solve for equilibrium). Price dispersion may arise from heterogeneity of consumer search costs, accompanied either with cost differences among sellers or mixed strategies aimed at targeting consumers with different levels of search costs. It may also arise from heterogeneity in demand for services that reduce search costs, with consumers that demand more services paying higher prices. Finally, temporal price dispersion may arise from seller efforts to learn the maximum price at which an item will sell.

While the mixed strategy explanation for price dispersion is commonly used, and there is some evidence that the identity of the minimum-priced seller does fluctuate through time, one must worry about the realism of this explanation. It seems questionable that sellers really do randomize their prices through time, although possibly this is a good approximation. Development of a model of pricing and price dispersion that is more closely related to actual seller behavior, and that incorporates services provided by the seller that may reduce search costs, would seem a good area for further research. Possibly, extension of the model of Carlson and McAfee (1983) to the case where sellers are differentiated on the services they offer would be a good way to proceed.

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6 Structural models of pricing

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Abstract

In this chapter, we first describe how structural pricing models are different from reduced-form models and what the advantages of using structural pricing models might be. Specifically, we discuss how structural models are based on behavioral assumptions of consumer and firm behavior, and how these behavioral assumptions translate to market outcomes. Specifying the model from these first principles of behavior makes these models useful for understanding the conditions under which observed market outcomes are generated. Based on the results, managers can conduct simulations to determine the optimal pricing policy should the underlying market conditions (customer tastes, competitive behavior, production costs etc.) change.

1. Introduction

Pricing is a critical marketing decision of a firm – witness this entire *Handbook* devoted to the topic. And increasingly, structural models of pricing are being used for understanding this important marketing decision, making them a critical element in the toolkit of researchers and managers. Starting in the early 1990s (for example see Horsky and Nelson, 1992), there has been a steady increase in structural modeling of pricing decisions in the marketing literature. These models have accounted for firm and consumer decision-making processes, with topics ranging from product-line pricing, channel pricing, non-linear pricing, price discrimination and so on (see Table 6.1 for a sample of these papers).

So what precisely are structural models of pricing? And how do they help the pricing decisions of a firm? In these models, researchers explicitly state the behaviors of agents based on economic or behavioral theory. In marketing, these agents are typically consumers and/or firms who interact in the market. Market data of quantity purchased and/or prices and other types of promotions are treated as outcomes of these interactions. In contrast to structural models, reduced-form models do not need to articulate precisely what behaviors of consumers and/or managers lead to the observed quantity purchased and/or market prices. There is a rich tradition of such reduced-form studies in marketing, with the profit impact of marketing strategies or PIMS studies as a leading example. In these studies, researchers examined how profits were affected by factors such as advertising and market concentration. Such reduced-form studies are very useful in establishing stylized facts (e.g. high firm concentration is associated with higher prices). Also, if the researcher's primary interest is in determining comparative statics (e.g. whether prices go up when excess capacity is more concentrated), reduced-form studies are perfectly adequate.

That said, there are several issues with these reduced-form models – the use of accounting data (which do not always capture economically relevant constructs, e.g. economic

* The chapter has benefited from excellent comments from a referee and the editor.

Table 6.1 A survey of structural pricing papers

Author	Pricing issue examined	Model	Managerially relevant findings
Besanko et al. (2003)	Third-degree price discrimination under competition by manufacturers and a retailer in the ketchup market	Demand side: aggregate logit model with latent-class heterogeneity structure Supply side: the retailer as a monopolist decides prices to maximizes the category profit while manufacturers maximize their profit by acting as a Stackelberg leader in the channel	The retailer can increase the profit by discriminating a finite number of customer segments; manufacturers are better off because of the retailer's use of price discrimination Price discrimination under competition does not lead to all-out price competition
Besanko et al. (1998)	Competitive pricing behavior of manufacturers in the yogurt and ketchup markets	Demand side: aggregate logit model Supply side: Bertrand–Nash pricing behavior by manufacturers and the common retailer	Firm can use alternative value creation strategies to accomplish competitive advantage
Che et al. (2007)	Competitive pricing behaviors of manufacturers and retailers when the demand is state-dependent in the breakfast cereal market	Demand side: logit model with a latent-class heterogeneity structure Supply side: menu of different pricing behaviors by manufacturers – Bertrand and collusive; menu of different interactions between manufacturers and the retailer – manufacturer Stackelberg and vertical Nash	Ignoring demand dependence will lead to wrong firm behavior inferences The observed retail pricing in this market is consistent with the assumption that manufacturers and retailers are one-period-forward-looking in price-setting
Chintagunta (2002)	Drivers of retailer pricing behavior in OTC analgesics category	Demand side: aggregate mixed logit model Supply side: retailers maximize the profit function by accounting for store retail competition, side payment and share of the store brand	The effects of different drivers differ across brands within the category
Chintagunta et al. (2003)	Price discrimination in a retail chain	Demand side: aggregate mixed logit model	Store-level pricing may increase firm's profit but not reduce consumers' surplus relative to chain-level pricing

Table 6.1 (continued)

Author	Pricing issue examined	Model	Managerially relevant findings
Chu et al. (2006)	Effects of various product bundle pricing strategies, including bundle-size pricing[a] (BSP), discounted component pricing[b] (DCP), mixed bundling and simple component pricing	Demand side: the market share for each option is derived from consumer utility maximization while consumers' preferences are assumed to follow bimodal normal distribution	Bundling strategies like BSP and DCP dominate simple component pricing. Although fewer bundles are offered, DCP can generate almost the same profit as mixed bundling. BSP is also a profitable pricing strategy
Draganska and Jain (2005)	Optimal pricing strategies across product lines and within product lines in the yogurt industry	Demand side: aggregate nested logit model with latent-class heterogeneity structure Supply side: Bertrand–Nash pricing behavior by manufacturers and the common retailer	Pricing differently across product lines but uniformly within product lines is an optimal strategy, which is consistent with current pricing practice
Iyengar (2006)	Increasing block pricing (three-part tariff pricing) in the wireless service industry in USA	Demand side: mixed logit model	Changes in access price affect consumer churn and long-term profitability more than changes in marginal prices Changes in access prices affect the CLV of the light users more than that of the heavy users
Kadiyali et al. (1996)	Product line pricing in the laundry detergents market	Demand side: linear function of prices and other variables Supply side: menu of different pricing strategy assumptions – Bertrand–Nash, Stackelberg etc.	Stackelberg leader–follower pricing better explains data than Bertrand–Nash pricing. Each firm positions its strong brand as a Stackelberg leader, with the rival's minor brand being the follower
Lambrecht et al. (2007)	The impact of demand uncertainty on how consumers choose Internet service plans	Demand side: mixed logit model	Demand uncertainty drives the consumer plan choice, which favors three-part tariffs Three-part tariff will increase firm's profit but reduce consumer surplus

Table 6.1 (continued)

Author	Pricing issue examined	Model	Managerially relevant findings
Leslie (2004)	Monopoly second- and third-degree price discrimination of Broadway theaters	Demand side: aggregate mixed logit model	Observed practices of price discrimination increase firms' profit by 5% relative to uniform pricing. The theater can further improve firms' profit if they offer 30% discount instead of the current 50% Consumer welfare gain from price discrimination is relatively small
McManus (2004)	Second-degree price discrimination under competition in specialty coffee market	Demand side: aggregate mixed logit model	Quality distortion is the lowest for the top qualities, which is consistent with economic theory
Narayanan et al. (2007)	Two-part tariff pricing in the telecommunication industry	Demand side: random coefficient probit model, accounts for consumer learning	Consumers learn much faster when they are on the measured plan than when they are on the fixed plan
Pancras and Sudhir (2007)	Evaluate the optimal customer, product and pricing strategy for the coupon service provided by Catalina in the ketchup market	Demand side: logit model with a latent-class heterogeneity structure Supply side: the retailer sets prices to maximize category profits given the manufacturer's decision to buy one-to-one coupon service. The manufacturer sets wholesale price and the coupons' face value to consumers	Catalina can increase its profit by selling nonexclusively Catalina can increase the profit by using longer purchase history data to target Retailer will benefit from undercutting the prices of Catalina for the one-to-one service
Richards (2007)	Strategic pricing promotion in perishable product market	Demand side: nested logit model Supply side: multiproduct retailers maximize profits by making strategic decisions including shelf price, promotion price and frequency of promotion	Retailers set prices and promotion strategies moderately cooperatively, which is less competitive than Bertrand Price promotions affect store revenue most when stores are highly substitutable but products are not

Table 6.1 (continued)

Author	Pricing issue examined	Model	Managerially relevant findings
Roy et al. (1994)	Competitive pricing in the US automobile market	Demand side: a function of lagged quantities and current prices Supply side: firms choose prices to minimize the difference between the real sales and the preset target	Stackelberg leader–follower game is more consistent with the pricing behavior in some segments of the US automobile market than Bertrand–Nash pricing
Sudhir (2001)	Competitive pricing behavior in various segments of the automobile market	Demand side: aggregate mixed logit model Supply side: firms maximize the profit by allowing a menu of possible pricing behaviors	The larger car and luxury segments show evidence of more collusive pricing; the small car segment is much more competitive
Sudhir et al. (2005)	How prices change with changes in demand, costs and competition in the US photographic film industry	Demand side: aggregate mixed logit model Supply side: Bertrand pricing behavior by firms	Competitive intensity is higher in periods of high demand and low cost The information of competitor prices can help determine how demand and cost conditions affect the competitive intensity
Verboven (2002)	Quality-based price discrimination in the European car market	Demand side: aggregate mixed logit model Supply side: pricing difference is the sum of the marginal cost differences and mark-up differences	Find evidence to support the existence of the second-degree price discrimination between high- and low-mileage drivers
Xiao et al. (2007)	Service bundles (voice and text services) under three-part tariff pricing in the wireless market	Demand side: mixed logit model accounting for switching cost and learning	Consumer preference for voice call is positively correlated with that for text Changes in switching cost or consumers' information of own usage preferences significantly affect the penetration of the two service plans offered by the firm

Notes:
[a] Bundle-size pricing means that firm sets prices that depend only on the number of products purchased.
[b] Discounted component pricing means that firm sets component pricing and offers discounts by the total number of products purchased at the same time.

profits are not the same as accounting profits) and the reverse causality issue. As an example of the latter, estimating a simple market demand function treating firm prices as exogenous ignores the fact that a change of the firm's pricing decisions may be caused by a change in the market environment, such as competition and consumer preference. Another important issue with reduced-form models relates to Lucas's critique – the behavior of players (firms or consumers) is likely to be a function of the behaviors of other players. For example, if firms are in a price war, consumers may come to expect low prices and will change their shopping behaviors accordingly. If firms are able to stop this price war, how might the behaviors of consumers change as their price expectations change? These issues cannot be addressed with reduced-form models unless we have reasonable assumptions about the behaviors of consumers and/or firms in the market and unless we have regime-invariant estimates of consumer behavior.

In contrast, using the structural approach to build pricing models, we assume that the observed market outcomes such as quantity sales and/or prices are generated from some explicit economic or behavioral theory of consumers' and firms' behaviors. There is an explicit linkage between theory and empirics. To build theory models of pricing (e.g. for third-degree price discrimination) that are tractable, researchers usually have to choose simple demand specifications and firm-conduct specifications. To understand comparative statics in such models, researchers sometimes also have to resort to selecting what might seem like arbitrary parameter values and conduct numerical simulations. An advantage of structural empirical models is that they can build realistic consumer and firm behavior models, and estimate them even when the models are intractable. Parameter estimates are obtained from actual data and linked to behavioral interpretations. The estimated parameters can then provide a sound basis for conducting policy simulations, such as understanding the impact of new pricing policies from existing firms, entry and exit, mergers and acquisitions and so on, and, based on that, provide managerial recommendations that might not be possible using the reduced-form approach.

This is especially true if the policy experiments are related to new price regimes, i.e. prices assumed in experiments are out of the range of the current sample data. This is because a reduced-form regression model typically tries to match the model with the observed data; there is no guarantee that the model will still perform well when new prices lie outside the range of the current data. Further, when the data are incomplete researchers can sometimes impose restrictions based on economic theory to recover the parameters they are interested in. A typical example in marketing is to infer marginal costs based on pricing equations. Thomadsen (2007) demonstrated that using a structural model, one can infer the demand and production functions in the fast-food industry solely from observed prices (and not units sold or market shares). One major constraint of structural models is the need to impose potentially restrictive behavioral assumptions. Hence they might be less flexible compared with the reduced-form approach; researchers should examine the reasonableness of these assumptions from the data.

It is important to recognize that the distinction between a structural model of pricing and its reduced-form counterpart is less stark. That is, structural modeling is really a continuum where more details of consumer and firm behaviors are modeled, as data and estimation methodology permit. Most empirical models lie between 'pure' reduced-form and structural models. For example, if pricing is the real interest, researchers may focus

on modeling how the behaviors of consumers are affected by the firm pricing strategies, or how firms compete in the market through pricing strategies, and treat the impact of other firm strategies such as advertising and non-price promotions in a reduced-form manner as simple control variables (see Chintagunta et al., 2006b). On the other hand, we should also recognize that some sort of causal relationships are implicitly assumed in most reduced-form models, especially when the results lead to policy recommendations. Suppose a researcher estimates a simple model of price as a function of firm concentration, and uses the result to infer the optimal price for a firm. This researcher assumes that concentration changes prices and not the other way round. Further, the assumption of firm behavior is current period profit or revenue maximization. When the researcher suspects that there may be a correlation between the error term and the price in the regression model, instrumental variables may be used in model estimation. However, the choice of instrumental variables implies certain assumptions about why they are correlated with prices and not the error term in the model. In summary, the major difference between structural and reduced-form models is whether behavioral assumptions are explicitly specified in the model (see detailed discussion in Pakes, 2003).

We now turn to the discussion of various parts of a structural model. The purpose of this chapter is not to provide an exhaustive survey of the marketing literature. We select some marketing and economic works in our discussion for illustration purposes, and refer the reader to Chintagunta et al. (2006b), which provides a more complete survey. Our purpose here is to explain the procedure of building a structural model that relates to pricing issues in marketing, and to discuss some important but understudied issues. For greater detail, especially on econometric issues, we refer the reader to excellent surveys in Reiss and Wolak (2007) and Ackerberg et al. (2007).

We first discuss in the next section the four basic steps in constructing a structural pricing model, which involves (1) specifying model primitives including consumer preferences and/or firm production technologies; (2) specifying the maximands or objective functions for consumers and/or firms; (3) specifying model decision variables, which include consumers' quantity purchased and/or firms' pricing decisions. Sometimes other strategic decisions such as advertising, display promotions etc. will also be modeled. The final step is (4) specifying price-setting interactions, i.e. how firms compete against each other through setting prices. With this structural model we explore further issues in model estimation and application, including (1) the two major types of error terms that researchers typically add in the estimation model and their implications; (2) various techniques used in the econometric estimation and other issues such as endogeneity, the choice of instruments and model identification; (3) model specification analysis, i.e. the test of the behavioral assumptions in the model; and (4) policy analysis based on the estimation results. We also discuss some general marketing applications of the structural model there. Finally we conclude and offer some thoughts on future research directions.

2. Specifying a structural pricing model

We use two papers as illustrations to show various aspects of structural modeling for setting prices. These are the studies by Besanko et al. (2003) on competitive price discrimination and Xiao et al. (2007) on pricing for wireless services in the communication industry. Competitive price discrimination cannot be grasped without an understanding

of underlying consumer behaviors and firm strategies. Therefore Besanko et al. build a consumer choice model with the assumption of utility maximization. Further, manufacturers and retailer price decisions are modeled as the outcome of profit maximization, with dependencies between them explicitly modeled. Besanko et al. use model estimates to conduct policy simulations, as we discuss in later sections.

Xiao et al.'s study of wireless pricing includes an analysis of three-part tariff pricing (a fixed fee, a free usage and a marginal price that is charged with usage above the free usage) is typically used in the industry. Firms in the industry also typically offer consumers service plans that bundle several services such as voice and text message. In their data, the focal firm introduced a new service plan in the middle of the sample period. While most consumers finally choose the service plan that minimizes the total cost conditional on their observed usages, switching from one to another service plan took time. It is difficult to use a reduced-form demand model of service plans to estimate the data given the complex pricing structure and the entry of the new plan during the sample period. The authors therefore build a structural model in which consumers choose a service plan that maximizes their utility. The authors are agnostic about the firm pricing strategy; however, based on their estimated consumers' responses to the new service bundle under a three-part tariff they are able to explore interesting managerial issues such as whether or not bundling services in a plan under a three-part tariff will be more profitable than selling services separately under various pricing mechanisms, including linear and two-part tariff pricing. They can further compute the optimal pricing structure based on estimated consumer preference.

In anticipation of the coming discussion, Table 6.2 lists the steps needed to build a structural model and provides a quick summary of how our two illustrative papers perform each of these steps.

2.1 Specifying model primitives

As mentioned in the introduction, the starting point of a structural model is to specify the behaviors of the agents being studied. In Besanko et al. the agents being studied are consumers, retailers and manufacturers, whereas in Xiao et al. the focus is consumer choice behavior for wireless service plans; therefore the agents studied are only consumers.

A structural model usually begins with the following model primitives: consumer preferences and firm production technologies. Consumer preferences are a function of variables exogenous to them, such as attributes of products, and variables that are decision outcomes of firms such as market prices. Firms face factor prices that are exogenous to them. A richer model usually allows for heterogeneity in the consumer preferences and/or firm technologies. It is important to identify which variables in the data are assumed to be exogenous and which are not, and examine how reasonable these assumptions are. In this way we make the implied causality explicit (i.e. changes in exogenous variables cause changes in endogenous variables), and also examine how restrictive the model assumptions are. For example, it might be reasonable for researchers to assume product attributes as exogenous given a sufficiently short time horizon, but allow pricing and other promotion decisions to be endogenous, resulting from consumer preferences and the production technologies and competition behaviors of firms based on these primitives. Another example is that in the short run it is reasonable to treat the number of competitors as exogenous. Pricing decisions do not depend on fixed costs. This is a common

Table 6.2 Steps in building a structural model: Bensanko et al. and Xiao et al.

Step in modeling	Besanko et al.	Xiao et al.
Specify model primitives	Heterogeneity of consumers' preferences for ketchup products, cost functions faced by retailers and manufacturers	Heterogeneity of consumer preferences for voice and text offered from wireless phone
Specify agent maximands	Consumers maximize utility; retailers and manufacturers maximize profits	Consumers maximize utility under nonlinear pricing and budget constraint
Specify model decision variable	Consumers choose which brand to purchase; manufacturers choose wholesale price; retailer chooses retail price	Consumers choose service plan at the beginning of the period, then choose usage levels for both voice and text
Model price-setting interactions	Consumers are price-takers; Stackelberg game between manufacturers and retailer, Bertrand–Nash price competition among manufacturers	Consumers are price price-takers; firm behavior is not modeled

assumption used in most of the structural pricing models in marketing. However, in the long run, entry and exit can be expected to happen. Fixed costs can affect the number of competing firms in a market and hence also market prices.

Besanko et al. model the consumer preference for ketchup products. They allow for latent class consumer heterogeneity in brand preferences as well as responsiveness to marketing variables including price. They assume an exogenous number of manufacturers in the ketchup market and a monopoly retailer. Each manufacturer may produce several brands and must sell their products through the retailer. The marginal cost of producing one unit of the product is constant and differs across the manufacturers. The marginal cost of selling one unit of the product is the wholesale price charged by the manufacturers. They assume that other costs for the retailer are fixed costs. Fixed costs of manufacturers and the retailer have no impact on market prices in their data. Further discussion of the details of the model is provided below.

The consumer utility in Xiao et al. is a function of the consumption of two types of services – voice and text message usages (voice and text henceforward). They assume that the preferences for the two services are continuously distributed, and these preferences might be correlated. The assumption of the preference distributions for the two services is important as they determine the firm's optimal bundling and non-linear pricing strategies to target different consumer segments. The firm decision of new service plan introduction is treated as exogenous. Because the charges for the two service plans vary according to the specific levels of access fee, free usages and marginal prices, the consumer cost will be different depending on the usage levels of voice and text and which service plan they sign up to. Again, further discussion of the details of the model is provided below.

2.2 Specifying agent maximands

Next, modelers specify objective functions for agents. Objective functions can be treated as a bridge connecting the changes of exogenous variables to changes of endogenous variables that we are interested in (quantity purchased, prices etc.) Consumers are typically modeled as utility maximization agents within a time horizon. The time horizon can vary from single period to infinite period. Firms are typically assumed to maximize profits, again within a single or infinite period. They are called dynamic models if multiple periods are involved and there exists linkage between current (purchase or pricing) decisions and state variables in future periods that will affect the utility or profit function; otherwise they are called static models. The major examples we discuss in this chapter are static models. We refer readers interested in dynamic models to another review paper by Chintagunta et al. (2006b). We visit the dynamic issues in the conclusion section.

The assumptions of the objective functions of consumers and firms in Besanko et al. are common in most marketing papers on pricing strategy. On the demand side, they assume that myopic consumers maximize their utility from purchasing brand j on each shopping trip. The indirect utility for consumer i from brand j on shopping trip t, u_{ijt} is given by

$$u_{ijt} = \gamma_{ij} + x_{jt}\beta_i - \alpha_i p_{jt} + \xi_{jt} + \varepsilon_{ijt} \tag{6.1}$$

where γ_{ij} is consumer i's brand preference, α_i is consumer i's sensitivity to price p_{jt}. The parameter β_i measures consumer i's responsiveness to other marketing variables x_{jt} such as feature and display. The indirect utility for the outside option is normalized to be mean zero with a random component ε_{i0t}. The myopic consumer assumption may be reasonable for ketchup, given that it is a small-price item in the shopping basket. A latent-class structure is used to capture consumer heterogeneity: there are K latent-class consumer segments, and every segment has its own parameters $(\gamma_{ij}^k, \beta_i^k, \alpha_i^k)$ and a probability weight λ^k, $k = 1, \ldots, K$. On the supply side, the manufacturer is assumed to maximize her current period profit by charging wholesale prices for her products, given other manufacturers' pricing strategies and the expected retailer's reaction to wholesale prices. The monopoly retailer is assumed to maximize her profit conditional on manufacturers' wholesale prices. The monopoly retailer r's objective function is modeled as follows:

$$\Pi_r = \sum_{j=1}^{J} (p_j - w_j) \sum_{k=1}^{K} \lambda^k S_j^k M \tag{6.2}$$

The manufacturer m's objective function is the following:

$$\Pi_m = \sum_{j \in B_m} (w_j - mc_j) \sum_{k=1}^{K} \lambda^k S_j^k M \tag{6.3}$$

where p_j is the retail price for brand j, w_j is the wholesale price, mc_j is the marginal cost, λ^k is the size of segment k, S_j^k is the share for brand j within segment k, and B_m is the number of brands offered by manufacturer m with $\sum_m B_m = J$. Finally, M is the quantity of total potential demand in the local market.

In Xiao et al., consumers are assumed to choose a service plan at the beginning of each period to maximize the expected utility within the period (rather than maximize intertemporal utility). If consumer i chooses a service plan j, $j = 1, \ldots, J$, from the focal firm at time t, she will then choose the number of voice minutes x_{it}^V, the number of text messages

x_{it}^D, and quantity of the outside good x_{it}^0 which is the consumption of products and services other than the wireless services. To consume a bundle $\{x_{it}^V, x_{it}^D\}$ from service plan j, the consumer pays an access fee A_j, enjoys a free usage for voice F_j^V and for text F_j^D, and then pays a marginal price for voice p_j^V if $x_{it}^V > F_j^V$, and for text p_j^D if $x_{it}^D > F_j^D$. The authors assume that the utility function is additively separable in voice and text. The consumer's direct utility from the consumption and choosing the service plan, $U_j^i(x_{it}^0, x_{it}^V, x_{it}^D)$ is as follows:

$$\begin{aligned} &U_j^i(x_{it}^0, x_{it}^V, x_{it}^D) \\ &= \delta_j + x_{it}^0 + \left[\theta_{it}^V \beta_i^V x_{it}^V - \beta_i^V \frac{(x_{it}^V)^2}{2}\right] + \left[\theta_{it}^D \beta_i^D x_{it}^D - \beta_i^D \frac{(x_{it}^D)^2}{2}\right] + \varepsilon_{ijt} \end{aligned} \tag{6.4}$$

where δ_j is a plan-specific preference intercept. θ_{it}^L is the preference parameter of consuming service L, $L = \{V, D\}$, with the following specification:

$$\theta_{it}^L = \theta_i^L + \xi_{it}^L \tag{6.5}$$

where θ_i^L is the mean preference, and ξ_{it}^L is the time-varying usage shock. The heterogeneity of preferences $\theta_i \equiv (\theta_i^V, \theta_i^D)'$ among consumers is assumed to follow a continuous bivariate normal distribution with mean $(\overline{\theta}^V, \overline{\theta}^D)'$ and covariance matrix

$$\begin{bmatrix} \sigma_V^2 & \sigma_{VD} \\ \sigma_{VD} & \sigma_D^2 \end{bmatrix}.$$

Finally, β_i^L, $L = V, D$ are the price sensitivity parameters for voice and text, respectively. The consumer will maximize the above direct utility function subject to the budget constraint:

$$\begin{aligned} &\max_{\{x_{it}^0, x_{it}^V, x_{it}^D\}} U_j^i(x_{it}^0, x_{it}^V, x_{it}^D | d_{it} = j) \\ &\text{subject to } x_{it}^0 + [p_j^V \cdot (x_{it}^V - F_j^V)]\{x_{it}^V \geq F_j^V\} + [p_j^D \cdot (x_{it}^D - F_j^D)]\{x_{it}^D \geq F_j^D\} + A_j \leq Y_i \end{aligned} \tag{6.6}$$

where Y_i is the income of the consumer, and $\{\cdot\}$ is an indicator function that equals one if the logical expression inside is true, and zero otherwise. The variable d_{it} is the consumer's choice at time t. Solving this constrained utility maximization problem, Xiao et al. obtain the consumer's optimal usage decision x_{it}^{L*} as follows:

$$x_{it}^{L*} = \begin{cases} \theta_{it}^L - \dfrac{1}{\beta_i^L} p_j^L & \text{if } \left\{\theta_{it}^L > F_j^L + \dfrac{1}{\beta_i^L} p_j^L\right\} \\ F_j^L & \text{if } \left\{F_j^L < \theta_{it}^L \leq F_j^L + \dfrac{1}{\beta_i^L} p_j^L\right\}, L = V, D \\ \theta_{it}^L & \text{if } \{0 < \theta_{it}^L \leq F_j^L\} \\ 0 & \text{if } \{\theta_{it}^L \leq 0\} \end{cases} \tag{6.7}$$

The consumer's optimal usage is a non-linear function depending on which interval her θ_{it}^L is in. Plugging equation (6.7) into the direct utility function (6.4), the authors obtain consumer i's indirect utility $V_{j,it}$ from choosing the service plan j.

The above examples assume fully rational consumers and firms. Recently there has

been a call in marketing to incorporate psychological and sociological theories into modeling consumers' and firms' behaviors, e.g. including reference dependence, fairness, confirmatory bias (see Narasimhan et al., 2005). Such richer specifications will help to explain the observed data which may not be explained by standard economic theory – for example, market response to price increases versus decreases may be asymmetric. This may relate to reference dependence or other psychological factors.

On the firm behavior modeling front too, researchers have increasingly explored firms going beyond pure profit maximization. Chan et al. (2007) find that the manager of an art-performance theater has a larger preference weight for avant-garde shows, which is consistent with the center's mission statement. Sriram and Kadiyali (2006) study if retailers and manufacturers maximize a weighted combination of shares or sales and profits, and what impact this maximand and behavior have on price setting. They find that across three categories, there is evidence that these firms maximize more than pure profits; as expected, firms that care about sales or shares price lower and firms that have higher prices place a negative weight on sales or shares. Wang et al. (2006) model firm managers' objective function as a linear combination of expected profits and shareholder market value, and their empirical evidence supports this assumption. All three studies point to an issue with static supply-side models, i.e. the difficulty of capturing accurately in a static supply-side model the complexities of competitive pricing in a dynamic game. For example, firms can have long-run objectives that might be a combination of shares, profits, shareholder market value etc. In the short run, the firm might consider building market share and sacrificing profitability to do so, with the goal of market dominance and profitability in the longer run. Also, multiple forms of firm behavior are possible in dynamic games, e.g. entry deterrence, predatory pricing, etc. that are hard to capture in a simple static one-shot game.

Another important assumption in most structural pricing studies that deserves attention is the role of uncertainty or information set of both firms and consumers. The typical assumption has been that consumers know their preferences as well as firm prices, firms know the (distribution of) consumer preferences and their own and rivals' pricing strategies. For example, Besanko et al. (2003) assume that consumers know their own brand preferences and the prices charged by retailers, while firms have good knowledge about the underlying segment structure of consumer preferences (the discrete preference types). It seems a reasonable assumption for stable product markets in their paper. However, this assumption might be unrealistic in many instances. Consumers might be unaware of their own preferences given limited information. For example, Xiao et al. (2007) consider two types of consumer uncertainty: first, consumers do not know the usage shock ξ_{it}^{L} (see equation (6.5)) when they decide which service plan to choose at the beginning of each period. Second, consumers may not know their mean preference types θ_i; instead, they have to learn their preference over time by observing their usage experience. This behavior assumption is consistent with the fact in the data that consumers only switched to the new data-centric plan several periods after the plan had been introduced (some did not switch even at the end of the sample period) even when their benefits would be large had they switched earlier.

Consumers also may not have perfect information on attributes or quality and prices of all products available in the market. Firms might not know the precise distribution of consumer preferences, and might have incomplete knowledge of their own or rivals' production technologies and pricing strategies. Some structural pricing papers have

attempted to incorporate these alternative information set assumptions. Miravete (2002) provides empirical evidence of a significant asymmetry of information between consumers and the monopolist under different tariff pricing schemes in the telecommunication industry. We expect future pricing research to study the impact of limited information on either consumers' or firms' decision-making; the results from these studies are likely to be different from those from models with a perfect information assumption.

2.3 Specifying model decision variables

Given that this chapter is about structural models of pricing, price is of course the firm decision variable that we are focusing on. However, there are at least two layers of complexity in studying pricing – the depth in which pricing is studied, and whether other decision variables are studied simultaneously.

Several studies have examined the case of firms choosing a single price for each product. In Besanko et al. (2003), each manufacturer chooses one wholesale price for each of her own brands. The monopolist retailer decides the retail price for each brand conditional on the wholesale price. While modeling each firm as picking one price is an appropriate place for structural pricing studies to begin their inquiry, researchers must acknowledge that a more complicated pricing structure exists in most industries. Firms may optimize prices of product lines and for various customer segments. Similarly, pricing can be either linear, fixed fee, or a more complicated non-linear scheme. An increasing number of studies examines the issue of price discrimination (e.g. Verboven, 2002; Besanko et al., 2003; Miravete and Roller, 2003; Leslie, 2004; McManus, 2004). Further, pricing for multiple products (product line) leads to the possibility of bundling and charging different prices for different product bundles (e.g. Chu et al., 2006). Under these pricing schemes closed-form optimal solutions usually do not exist, and computational complexity has deterred research efforts in the past. However, with recent development in computation and econometric techniques, researchers are able to estimate complicated models. For instance, Xiao et al. (2007) used simulation-based methods to estimate the demand function for voice and text under service bundling with three-part tariffs. Based on these results they further compute the optimal pricing strategy for the firm under various scenarios.

The other issue in building structural models of price is whether price can be studied independently of other strategic choices of firms. Examples include the study of joint determination of price and advertising (Kadiyali, 1996) and study of the relationship between price and channel choice (Chen et al., 2008; Chu et al., 2007). Often, researchers are constrained by data and the complexity of modeling to examine such joint determination. An additional tricky issue is the possible difference in the periodicity of decision-making regarding price decisions versus other decisions, such as advertising or production capacity. If these decisions are made in different planning cycles, e.g. pricing being made weekly and advertising quarterly, it is difficult to estimate jointly optimal price and advertising rules with a different number of data points. Typically, researchers have assumed the same periodicity of such decisions (e.g. Vilcassim et al., 1999). Another alternative used is to examine the issue sequentially, e.g. studying the choice of price conditional on previous locational choice made by the firm when it entered the market (Venkataraman and Kadiyali, 2005). In this case the first-stage locational choice will take account of its impact on pricing in future periods, leading to a more complicated dynamic model setting.

2.4 Modeling price-setting interactions

Given assumptions about consumers and firms maximizing their objectives, how does the market equilibrium evolve and how do these decision-makers interact with one another? The typical assumption about consumer behavior has been price-taking. For firms, the default has been to assume one form of behavior such as Bertrand–Nash, Stackelberg leader–follower or collusive pricing game. An important point to bear in mind when imposing a particular assumption of how firms interact with each other is to justify why this is an appropriate assumption for the industry, given that the estimation results are very dependent on the assumption made. For example, Besanko et al. (2003) assume a manufacturer Stackelberg (MS) game on the supply side. On this assumption, the retailer chooses retail prices to maximize the objective function (equation 6.2) by taking the wholesale prices as given. The first-order condition for the retailer's objective function is

$$\sum_{j=1}^{J}(p_j - w_j)\left(\sum_{k=1}^{K}\lambda^k \frac{\partial S_j^k}{\partial p_{j'}} M\right) + \sum_{k=1}^{K}\lambda^k S_{j'}^k M = 0 \tag{6.8}$$

Manufacturers decide the wholesale prices to maximize the objective function (equation 6.3) by taking into account the retailer's response to wholesale prices, i.e. $\partial p_l/\partial w_j, j, l = 1, \ldots, J$. The first-order condition for a manufacturer with respect to a brand j' is

$$\sum_{j=1}^{J}(w_j - mc_j)\gamma_{jj'}\left(\sum_{k=1}^{K}\lambda^k \sum_{l=1}^{J}\frac{\partial S_j^k}{\partial p_l}\frac{\partial p_l}{\partial w_{j'}} M\right) + \sum_{k=1}^{K}\lambda^k S_{j'}^k M = 0 \tag{6.9}$$

where γ_{jj} is equal to one if brand j and j' are offered by the same manufacturer; otherwise it is equal to zero, and λ^k is the size of segment k, $k = 1, \ldots, K$.

As we discuss later, Besanko et al. demonstrate that the MS game is a reasonable assumption in their data. The manufacturers are selling in the national market, hence they are likely to be leaders in the vertical channel, while the retailer sells in a local market, so she is likely to be a follower. Further, the retailer sells for all manufacturers, so is assumed to maximize category profits. The monopolist retailer assumption is consistent with the conventional retailer wisdom that most consumers do grocery shopping at the same store.

An alternative to imposing an assumption of how firms interact with each other is to compare various alternative assumptions and let the data suggest which model best represents market outcomes. Gasmi et al. (1992) and Kadiyali (1996) are two of the few studies considering a menu of models (forms) and choosing the one that fits the data best. Gasmi et al. (1992) consider different firm conduct behaviors such as Nash in prices and advertising, Nash in prices and collusion in advertising, Stackelberg leader in price and advertising etc. when they analyze the soft-drink market using data on Coca-Cola and Pepsi-Cola from 1968 to 1986. Using a similar approach, Kadiyali (1996) analyzes pricing and advertising competition in the US photographic film industry.[1]

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[1] Other studies refer to Roy et al. (1994) and Vilcassim et al. (1999).

3. Estimating and testing a pricing structural model

3.1 Going from deterministic model to market outcomes

Outcomes from the economic models of utility and profit maximization are deterministic. In reality, given any parameter set these outcomes will not perfectly match with the observed prices and quantity purchased in the data. To justify these deviations, and hence to construct an econometric model that can be estimated from the data, researchers have typically added two types of errors: errors that capture agent's uncertainty and errors that capture researcher's uncertainty. The agent's uncertainty is when either consumers or firms (retailers and manufacturers) have incomplete information about marketplace variables that influence their objective functions. Researchers may or may not observe such an error term from their data. For example, before visiting a store consumers might know only the distribution of prices and not the exact prices in the store. The researcher's uncertainty stems from researchers not observing from the data some important variables that affect consumers' or firms' objective functions, but consumers and firms observe these variables and account for them in their optimization behavior. An example of such uncertainty is that shelf-space location of items inside a store may affect consumers' purchase decisions but researchers cannot observe shelf-space locations in the data. Such errors become the stochastic components in the structural models which help researchers to rationalize the deviations of predicted outcomes from their models from observed market data. Economic and managerial implications can be very different under these two error assumptions and, depending on the problem, justifying the distributional assumptions of these errors can be critical, as we discuss below.

In their paper, Besanko et al. (2003) assume researcher's uncertainty only and capture it in two kinds of error terms. One is ε_{ijt} in equation (6.1), which is consumer i's idiosyncratic utility for different product alternatives. This is to capture the factors that affect consumers' purchase decision but are unknown to researchers. Besanko et al. follow the standard assumption that ε_{ijt} is double exponentially distributed. Relying on this distribution assumption, the authors can obtain the probability of type k consumer purchasing brand $j(S_{jt}^k)$ as follows:

$$S_{jt}^k = \frac{\exp(\gamma_{ij} + x_{jt}\beta_i - \alpha_i p_{jt} + \xi_{jt})}{1 + \sum_{j=1}^{J} \exp(x_{jt}\beta^k - \alpha^k p_{jt} + \xi_{jt})} \tag{6.10}$$

Another error term takes account of the product attributes (e.g. coupon availability, national advertising etc.) observed by the consumers but not by the researchers. It is represented by ξ_{jt} in equation (6.1). There is no agent's uncertainty in their model – consumers know own ε_{ijt} and ξ_{jt}, while firms know ξ_{jt} for all brands and the distribution of ε_{ijt}. The existence of ξ_{jt} causes the endogeneity bias in estimation – since firms may take into account its impact on market demand when they make price decisions, it will lead to the potential correlation between firms' prices and ξ_{jt} in consumers' utility function. Ignoring this price endogenity issue in the estimation will lead to biased estimation results and further biased inferences. See Chintagunta et al. (2006a) for a detailed analysis of this issue. We further discuss how to solve this issue in later sections.

Xiao et al. (2007) include both researcher's uncertainty and agent's uncertainty in

their econometric model. One is ε_{ijt} in equation (6.4), which captures the researcher's uncertainty of factors that may affect the consumer's choice of service plan but are unobserved by researchers. Similar to Besanko et al. (2003), ε_{ijt} is assumed to follow the double exponential distribution. Another error term is ξ_{it}^{L} in equation (6.5), which is consumer i's time-varying preference shock of using service L, $L = V, D$. The exact value is assumed to be unknown to the consumer when she makes the service plan choice, and hence captures the agent's uncertainty. The consumer may also have uncertainty about her mean preference $\theta_i \equiv (\theta_i^V, \theta_i^D)'$. Hence, with uncertainties of θ_i and ξ_{it}^{L} the consumer has to form an expectation for her indirect utility function $V_{j,it}$ conditional on her information set Ω_{it}, which consists of her past usage experience, i.e. $E[V_{j,it}|\Omega_{it}]$. The consumer will choose the alternative with the highest expected indirect utility. For simplicity let us assume that there is no switching cost. Under the distribution assumption of ε_{ijt} we can write down the probability of consumer i choosing plan j as

$$prob_i(j) = \frac{\exp(E[V_{j,it}|\Omega_{it}])}{1 + \sum_{k=1}^{J}\exp(E[V_{k,it}|\Omega_{it}])} \tag{6.11}$$

Note the difference between (6.10) and (6.11). In Besanko et al.'s (2003) set-up there is no agent's uncertainty, i.e. firms know ξ_{jt} for sure; hence they do not need to form an expectation for $(\gamma_{ij} + x_{jt}\beta_i - \alpha_i p_{jt} + \xi_{jt})$.[2] In Xiao et al. (2007), because of the agent's uncertainty each consumer has to form a conditional expectation for $V_{j,it}$ when she makes the service plan choice. In contrast, when deciding how much voice and text to be used during the period, θ_{it} (see equation (6.5)) is fully revealed to the consumer. Hence there is no agent's uncertainty in the usage decisions (see equation (6.7)). The authors assume that the firm knows only the distribution of θ_i for all consumers and not for each individual consumer, the researchers' information on θ_i is exactly the same as the firm's. Further, any potential unobserved product attributes of the service plans in the data have been accounted for by the plan preference parameter δ_j in the utility function (this effect is assumed as fixed over time; see equation (6.4)). Hence there is no price endogeneity issue in estimating the market share function of service plans. However, if there is an aggregate demand shock (say, a sudden change in the trend of using text message among cellular users) observed by the firm but not by researchers, the pricing structure of the new data-centric plan can be correlated with such a shock, and the endogeneity issue will then arise.

Reiss and Wolak (2007) identify other sources of error terms that could be considered in future research. In general, it is fair to say that the treatment of the nature and source of errors has not received the attention that it merits.

3.2 Econometric estimation

Depending on the type of errors in the model, various econometric techniques have been used in model estimation. Simple OLS or the likelihood approach is widely used when the endogeneity issue does not arise. Structural models typically involve the estimation of simultaneous equation systems. For example, in Besanko et al. (2003) the model involves

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[2] Here Besanko et al. also implicitly assume that consumers know x_{jt} and p_{jt} for sure.

consumer choice, manufacturers' and the retailer's pricing decisions. In Xiao et al. (2007) the model involves both service plan choice and usage decisions. FIML (full information maximum likelihood) or method of moments has been widely used for estimating simultaneous equations. Advanced simulation-based techniques have been developed recently (e.g. see Gourieroux and Monfort, 1996) in model estimation when there is no closed-form expression of the first-order conditions or likelihood functions. For example, Xiao et al. (2007) find that there is no closed-form expression for the plan choice probability function (see equation (6.11)) when there are agent's uncertainty of own θ_i and preference shocks ξ_{it}. In the model estimation, therefore, they use the simulation approach to integrate out the distribution of θ_i (according to consumers' beliefs) and ξ_{it} to evaluate the probability $prob_i(j)$. In general, allowing for a richer type of errors in the model will complicate the computation of the likelihood of observed market outcomes, and in such situations researchers have to rely on simulation methods. Instead of the classical likelihood approach, marketing researchers have often used the Bayesian approach in model estimation, especially when they want to model a flexible distribution of consumer heterogeneity.

A thorny issue relates to the endogeneity or simultaneity problem when the error terms correlate with prices. In empirical input–output (IO) literature, such as in Berry (1994), Berry et al. (1995) and Nevo (2001), generalized method of moments (GMM) and simulated method of moments estimators are usually used. Various advanced methods including contraction mapping and simulation-based estimation have been developed. The general principle is to use instruments for the endogenous variable price in model estimation. An advantage of using instruments in GMM is that researchers do not need to specify *a priori* the joint distribution of the error terms (e.g. ξ_{jt} in Besanko et al., 2003) and the endogenous variable such as price in their model. Recently, there has been a revival in likelihood-based estimates with the rise of Bayesian estimation in tackling the simultaneity issue (Yang et al., 2003). Another issue relates to the existence of multiple equilibria in the model (this is especially true for many dynamic competition models), where the likelihood function is not well defined. GMM in this case is useful for model estimation since it only uses the optimality condition in any of the equilibria but remains agnostic about which equilibrium is chosen by the markets in data. See related discussion in Ackerberg et al. (2007).

The role of instruments is very important in the econometric estimation of structural pricing models. The requirements for a good instrumental variable are 'relevance', i.e. the variable has to be correlated with the endogenous variable such as price; and 'exogeneity', i.e. the variable has to be uncorrelated with the unobserved error term. If relevance is low, researchers will have weak instruments and the error in the estimation can be large. Without exogeneity the instruments are invalid and researchers will obtain inconsistent estimates. Hence researchers have to examine the quality of the instruments they choose according to these aspects. Because structural models explicitly specify how the data are generated based on behavioral assumptions and hence how error terms and decision variables such as price are potentially correlated in the model, it helps us to understand to what extent the chosen instruments are valid. For example, if firms are involved in Bertrand–Nash pricing competition and their objective is to maximize own profit, cost shifters will be relevant and valid instruments for price in the demand equation (Berry et al., 1995). Bresnahan et al. (1997) specify the 'principles of differentiation' instruments,

including counts and means of competing products produced by the same manufacturer and by different manufacturers, for price. They argue that their instruments will be valid under different types of non-cooperative games such as Bertrand and Cournot. Lagged prices are sometimes used as instruments for current prices if the error term is independent over time (e.g. see Villas-Boas and Winer, 1999).

The availability of good instruments is closely related to the identification issue in the model. Usually there are several important behavioral parameters that researchers are interested to estimate, and the others in the model are termed 'nuisance' parameters. Unless there is enough variation in data, the behavioral parameters may not be identifiable. For example, price coefficients in a structural model with both demand and supply functions may not be identified if there is no variation in cost variables (e.g. raw materials cost) across markets or across time periods. Identification is not simply a matter of statistical identification of ensuring exclusion restrictions or overidentification restrictions, but rather more of determining the underlying movement in various market drivers that enables identification. A classic example of such identification is Porter (1983). In a study of rail cartels that ship grain, Porter uses the exogenous shift in demand caused by whether lake steamers were in operation or not – if lakes were frozen, this substitute was not available and therefore rail shipment demand increased predictably. This exogenous shift in demand is easily observed by the cartel members. Therefore, when demand falls with the lake steamers operating, cartel members should not misinterpret the drop in their demand as stemming from another cartel member stealing customers by offering better prices secretly. Therefore this exogenous demand shift is an important instrument in inferring whether pricing is collusive or not. This example illustrates both the importance of finding exogenous demand or cost shifters, and using them in theoretically grounded ways to help identify the pricing strategy of firms rather than a simple statistical identification strategy.

Because of the potential correlation between price and ξ_{jt}, Besanko et al. (2003) would not be able to identify the price coefficient α_i unless they had good instruments for price (see equation (6.1)). They choose product characteristics and factor costs as instruments for prices, and use the GMM to estimate their model. They demonstrate the importance of taking account of the price endogeneity issue by estimating the model without considering it. They find that the price coefficient will be downward-biased in the latter case.

Xiao et al. (2007) face a data problem in identifying the price sensitivity parameters β_i^V and β_i^D in their model (see equation (6.4)) – there is no price variation in either of the service plans during the sample period. To solve this problem, for tractability they first assume that there is no heterogeneity in β_i^V and β_i^D. Then they use the fact that some consumers switch service plans during the sample period. Since the two service plans have different pricing structures, by switching plans these consumers face different marginal prices for voice and text in data. The change of usage levels, once above the free usage levels, of the same consumer will help to infer consumer sensitivity to price changes.

The restriction on agents' objective functions is sometimes necessary for model identification. Suppose one wants to allow for a richer specification with non-profit maximization objectives and other biases in the firm pricing decision, such a model may not be identified solely from the data of market prices and quantity demanded. Similarly a consumer choice model allowing for consumers' imperfect information or bounded rationality may not be identifiable from traditional scanner data. In this case one may need to use

other data sources such as self-reported consumers' expectation of future prices or firms' expectation of future profits or revenues (e.g. see Chan et al., 2007a and Horsky et al., 2007).[3] Alternatively, creative field experiments in which price variations are exogenously designed (e.g. see Drèze et al., 1994 and Anderson and Simester, 2004) can help to avoid the endogeneity issue. In these cases researchers are certain that observed prices are not affected by aggregate demand shocks; hence consumers' price sensitivity (short- or long-term) can be estimated without resorting to the structural approach.

3.3 Specification analysis

Related to the above discussion, specifications and hence the estimation results are very dependent on the behavioral assumptions made in the model. While some assumptions have to be made to build structure (e.g. the market demand functional form and the distribution assumption of unobserved errors), when researchers use the reduced-form approach they rely less on the specification of the behavioral assumptions; hence their models may be more flexible to fit with the data. Most studies using the structural approach have not shown too much due diligence in comparing alternative behavioral assumptions or justifying from managerial or other sources why their assumptions are justified. In this regard, some issues to keep in mind are mentioned below.

First, model fit should not be the only criterion in determining whether or not the model assumptions are reasonable. Indeed, if model fit is the only criterion, researchers will often find that reduced-form models dominate structural models whose functional specification relies heavily on restrictive behavioral assumptions. The objective of a structural pricing model should not always be to minimize statistical error but to minimize model assumption error. The former refers to the objective of finding the best fit with the data. The latter refers to identifying a set of economic and behavioral theories that makes sense in explaining the data-generating process. As mentioned in previous sections, some questions related to behavioral assumptions are: are firms competitive or colluding with each other? Are consumers or firms maximizing long-term profit or value functions? Is there asymmetric information between firms and consumers? Does learning better capture firm and consumer behavior than the assumption of perfect information? Are there some 'irrational' behaviors that can be explained by psychological or sociology theory? In deciding which assumption to choose, researchers might have to make a tradeoff in choosing a model that describes the market more reasonably, even if this might mean sacrificing the model fit. For example, Besanko et al. (2003) model the interactions between manufacturers and the retailer in the channel where manufacturers are Stackleberg price leaders. Even if the authors found that a model assuming the retailer as the Stackleberg price leader over national manufacturers fits better with the price data, they might not want to use such a specification, considering the market reality.

So if model fit is not always the best means to judge the performance of a pricing structural model, what is? An important test is whether the model assumptions lead to sensible results when we go from model assumptions to managerial recommendations. For

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[3] Another stream of literature uses bounded estimators when the structural parameters are not point-estimable.

example, Besanko et al. (2003) compared the equilibrium outcome under their specification with different alternative assumptions. The implied retail margins from their model are face valid and therefore support the feasibility of the manufacturer Stackelberg leader assumption. In another example Xiao et al. (2007) find that with consumer learning and switching cost in their model, they can explain why some consumers switch to the new service plan while the others do not. Another way to see whether results are sensible is to conduct policy simulations and see if those results are sensible. We discuss more on this below.

3.4 Policy analysis

As discussed above, by building the structural model to analyze the underlying consumer preferences and firms' pricing decisions, we can use the structural analyses to answer some questions which cannot be addressed by reduced-form analysis precisely. Specifically, the results of a structural model can be used to conduct managerially useful simulation exercises. These exercises are valuable because the assumed policies can be out of sample (prices set at a level away from the sample observations, change in the mode of interactions between firms and consumers, entry and exit in the market, new government restrictions, and hypothetical consumer preference structure etc.) and will not be subject to the Lucas critique.

Besanko et al. (2003) assume that the retailer sets a uniform price in the model. Based on their demand and supply system estimates, they simulate the effects of two kinds of third-degree price discrimination, which are initiated by either the retailer or manufacturers. Retailer-initiated price discrimination means that the retailer sets segment-specific prices to maximize her profits. Manufacturer-initiated price discrimination means that manufacturers induce the retailer to charge segment-specific prices by offering her scanback discounts. The policy experiments show that firms can increase profit by discriminating a finite number of customer segments under both cases. So in this empirical analysis, price discrimination under competition does not lead to all-out competition (i.e. prices lower than uniform pricing strategy). Allowing for both vertical product differentiation and horizontal differentiation, they find empirical evidence that is against the theoretical finding that price discrimination under competition will lead to the prisoner's dilemma. This provides important managerial insights.

Xiao et al. (2007) illustrate how the firm may use its estimation result of the consumer preferences for voice and text to better segment the market. In particular, they find that preferences for voice and text are weakly positively correlated, indicating that a consumer with high preference for voice is more likely to have high preference for text. Based on their results they calculate the market response to changes in the three-part tariff structure, i.e. access fee, free usages and marginal prices. Finally they compute the optimal pricing structure for the two service plans, and predict the types of consumers, in terms of preferences for voice and text, that each service plan will be able to attract. They further compare the result with the predicted profits when the firm charges a two-part tariff under the bundling case, and when the firm charges two- and three-part tariffs but without bundling the two services. They find that a computed optimal three-part tariff under bundling generates about 38 percent higher revenue than at the current prices, although expected market share is 10 percent lower. Compared with the optimal prices without bundling, the three-part tariff will generate about 8 percent higher revenue. The impact on consumer welfare may vary depending on the consumer segments.

More examples covering different aspects of policy simulations relating to pricing can be found. For example, in addition to Xiao et al. above, Leslie (2004), Lambrecht et al. (2007) and Iyengar (2006) consider non-linear pricing. Draganska and Jain (2005) study the optimal pricing strategies across and within product lines in the yogurt industry. A similar analysis of product-line pricing and assortment decisions is in Draganska et al. (2007). Two papers that cover policy analyses with channel changes are Chen et al. (2008) and Chu et al. (2006). As all these examples indicate, policy analyses form the core of the managerially useful output of structural pricing studies.

4. Summary

Structural models of pricing can be useful in understanding the consumer- and firm-based drivers of market prices. They can also be useful in generating robust and managerially useful implications. That said, given the criticality of behavioral assumptions and instrumental variables in structural price models, researchers need to justify the use of these with great care. More careful analysis of the issues of model comparison and model identification by checking with the data will also be very useful. Yet another area in which structural models can be improved is the modeling of behavioral issues in pricing, relating to both consumers and firms. This is becoming more important following the call to incorporate psychological and sociological theory to better explain the consumer and firm behaviors. Narasimhan et al. (2005) discuss how, despite the demonstration of a variety of behavioral anomalies, very few theoretical models have attempted to incorporate these in their formulation. The same is true of structural pricing work. An exception is Conlin et al. (2007), who show that people are over-influenced by the weather on the day that they make their clothing purchases (rather than accurately forecasting the weather for the days of actual usage of the clothing item).

One way to allow for modeling behavioral issues is to enrich data sources. Additional data may be necessary for researchers to identify a richer set of behavioral assumptions from the data. For example, if we want to model how firms form expectations about their rivals' pricing strategy, we might need to supplement market data with surveys. An example of such a study is Chan et al. (2007a), who use the managerial self-reported expectations of ticket sales and advertising expenditures to understand the bias and uncertainty of managers when they make advertising decisions. Bajari and Hortacsu (2005) use lab experiment data to test if rational economic theories can explain economic outcomes in auction markets. If such data are difficult to obtain, researchers need, at the least, to acknowledge how the behavioral assumptions in their structural models can be tested with additional data.

This summary would be incomplete without consideration of alternatives to structural models of pricing. Reduced-form methods might be useful in providing stylized facts about pricing and other market outcomes. For example, Kadiyali et al. (2007) find that in real-estate deals where the buyer's agent and the seller's agent work for the same company, list prices are strategically set higher (and result in higher sales prices). A full model of buyer and seller dynamics, including the role for buyer and seller agents, accounting for endogenous entries and exits is beyond current methodologies. However, it is still useful to establish these stylized facts because they might reveal market inefficiencies that are important to both buyers and sellers and antitrust authorities. Similarly, natural experiments-based reduced-form models, e.g. Ailawadi et al.'s (2001) research on

P&G's switch to EDLP (everyday low pricing), offer very interesting avenues for understanding markets when full models are hard to build. For other marketing applications also see Drèze et al. (1994) and Anderson and Simester (2004). We expect that, in the future, marketing researchers will spend more effort in data collection though various sources such as survey and lab or natural experiments, and use these additional data to identify a richer set of behavioral assumptions in their models.

Interesting managerial implications may be generated from dynamically modeling the consumer choice and firm pricing behavior. Some of the marketing applications of dynamic models, such as Erdem et al. (2003), Sun (2005), Hendel and Nevo (2006) and Chan et al. (2007b), study how consumers' price expectations change their purchase and inventory-holding behaviors. In the dynamic competition games among firms, the equilibrium concept is typically Markov-perfect Nash equilibrium; that is, agents maximize an objective function, taking into account other agents' behavior and the effect of their current decisions on future state variables (e.g. market share, brand equity and productivity). A wide variety of strategies may be adopted, and some of the equilibrium outcomes are very difficult to model or compute. There has not been much empirical application in the literature due to these issues. However, with the recent development of computation and econometric techniques we start to see growing interest in academic research. For example, Nair (2007) studies the skimming strategies for video games, and Che et al. (2007) study pricing competition when consumer demand is state-dependent (e.g. switching cost, inertia or variety-seeking in consumer behavior) in the breakfast cereal market. These authors have made some interesting findings that would not have emerged from the static models. Studying the interactions of policies with a short-term impact on profitability such as price promotion and others with a long-term impact such as location and R&D investment decisions under the dynamic framework is another important area for future research. Finally, due to the computation complexity researchers might have to make some reduced-form assumptions in their models (e.g. reduced-form price expectation or demand function), and focus on the structural aspect of the strategic behaviors such as strategic inventory-holding among households or entry and exit decisions of firms. As a result the difference between the structural and the reduced-form approach is even less stark, as we discussed in the introduction.

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7 Heuristics in numerical cognition: implications for pricing

Manoj Thomas and Vicki Morwitz

Abstract

In this chapter we review two distinct streams of literature, the numerical cognition literature and the judgment and decision-making literature, to understand the psychological mechanisms that underlie consumers' responses to prices. The judgment and decision-making literature identifies three heuristics that manifest in many everyday judgments and decisions – anchoring, representativeness and availability. We suggest that these heuristics also influence judgments consumers make concerning the magnitude of prices. We discuss three specific instances of these heuristics: the left-digit anchoring effect, the precision effect, and the ease of computation effect respectively. The left-digit anchoring effect refers to the observation that people tend to incorrectly judge the difference between \$4.00 and \$2.99 to be larger than that between \$4.01 and \$3.00. The precision effect reflects the influence of the representativeness of digit patterns on magnitude judgments. Larger magnitudes are usually rounded and therefore have many zeros, whereas smaller magnitudes are usually expressed as precise numbers; so relying on the representativeness of digit patterns can make people incorrectly judge a price of \$391 534 to be lower than a price of \$390 000. The ease of computation effect shows that magnitude judgments are based not only on the output of a mental computation, but also on its experienced ease or difficulty. Usually it is easier to compare two dissimilar magnitudes than two similar magnitudes; overuse of this heuristic can make people incorrectly judge the difference to be larger for pairs with easier computations (e.g. \$5.00–\$4.00) than for pairs with difficult computations (e.g. \$4.97–\$3.96). These, and the other reviewed results, reveal that price magnitude judgments entail not only deliberative rule-based processes but also instinctive associative processes.

Introduction

The seminal work by Tversky and Kahneman (1974) and Kahneman and Tversky (2000) has identified a set of reasoning heuristics that appear to characterize much of people's everyday judgments and decision-making. Three heuristics, presumably because of their ubiquity, have particularly attracted the attention of researchers – anchoring, availability and representativeness. In this chapter, we review these three heuristics in the context of price cognition. We use the term price cognition as a generic term to refer to the cognitive processes that underlie consumers' judgments concerning the magnitude of a price and their judgments of the magnitude of the difference between two prices. Price magnitude judgment refers to a buyer's subjective assessment of the extent to which an offered price is low or high. Judgments of the magnitude of the difference between two prices are required in many purchase situations; for example, when buyers compare two products, or when they assess the difference between a regular price and sale price of a product on sale.

Price cognition plays a pivotal role in models of consumer behavior postulated in the economics as well as the psychology literature (Monroe, 2003; Winer, 2006). Both streams of literature concur on the following assumption: a buyer's subjective judgment of the magnitude of a price is an important determinant in purchase decisions. However, economists and psychologists differ in the way they characterize the manner in which buyers process the price information. The following two assumptions play a

fundamental, though often implicit, role in traditional models of buyer behavior posited by economists: (i) people are aware of the factors that influence their price cognition; and (ii) biases in judgments are caused by volitional inattention or cognitive miserliness and therefore can be prevented at will. In this chapter, we challenge these assumptions about awareness and intentionality (of biases) in price cognition. We begin by reviewing the numerical cognition literature to characterize the price cognition process. We then review evidence to suggest that price magnitude judgments entail not only deliberative rule-based processes, but also instinctive associative processes often referred to as heuristics. Specifically, in this chapter we discuss how anchoring, availability and representativeness heuristics affect the price cognition process.

Our choice of the 'heuristics in numerical cognition' approach to understanding price cognition has been guided by two major considerations. First, we believe an informed characterization of the price cognition process calls for an integration of the numerical cognition literature and the judgment and decision-making literature. Second, the heuristics in the numerical cognition approach could offer a unifying framework to discuss the many seemingly unrelated effects reported in the pricing literature. We explicate each of these considerations in some detail.

First, in order to critically examine the issues of awareness and intentionality in price cognition, we need to examine the two issues in the terms of the underlying representations as well as the processes that operate on these representations.[1] The questions about representations are: what are the different forms in which a multi-digit price is represented in consumers' minds? Are price magnitude judgments based on analog representations or on symbolic representations? The questions about process are: what processes operate on the different types of representations? Are these processes deliberative and rule-based or instinctive and associative? To answer these questions, we review the numerical cognition literature, and then the judgment and decision-making (JDM) literature. The numerical cognition literature elucidates how numbers are represented in people's minds, and some of the basic, lower-level processes that operate on these representations. Research on numerical cognition tends to draw inferences from meticulous analyses of response latency patterns measured down to the milliseconds and error rates in sterile[2] numerical tasks such as binary magnitude judgments and parity judgments. For example, in a typical magnitude judgment task, several numbers are flashed on a computer screen in a random order, and participants have to quickly indicate whether the stimuli are higher or lower than another number, the comparison standard. In a parity judgment task, instead of making magnitude judgments, participants have to indicate whether the stimuli are odd or even. Using such tasks, numerical cognition researchers study how various factors such as magnitude, distance from a comparison standard, and response codes affect participants' response time and error rates. Several robust and reliable effects have emerged from this stream of research: the distance effect (Moyer and Landauer, 1967), the problem size effect (Ashcraft, 1995), the size congruity effect (Henik and Tzelgov,

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[1] See Markman (1999) for a discussion on the distinction between symbolic and analog representations of knowledge, and the implications of this distinction for the processes that operate on these representations.

[2] We describe them as sterile because it could be argued that many of these tasks are not presented in a practical context and are not representative of everyday judgments.

1982), and the spatial–numerical association effect (also referred to as SNARC; Dehaene et al., 1993), etc. Offering a parsimonious and coherent account for all these effects using the same framework has proved to be a challenge. Competing theoretical models of representations and processing of numerical information continue to strive towards this goal (Dehaene, 1992; McCloskey and Macaruso, 1995).

In contrast, the JDM research tends to be concerned with methods for discerning the nature of everyday judgments and deviations from normative behavior. The JDM literature offers a richer characterization of the cognitive rules that people use in everyday judgments. Research of this nature draws on economics in addition to social and cognitive psychology. Thus the integration of the numerical cognition and the JDM streams of literature, we believe, is not only useful but also necessary for the understanding of the price cognition process.

Second, the heuristics in the numerical cognition approach could serve as a unifying framework for the behavioral pricing literature. To illustrate with an example, research has shown that people's judgments of the magnitude of price differences are anchored on the left-most digits of the prices (Thomas and Morwitz, 2005). People incorrectly judge the difference between 6.00 and 4.95 to be larger than that between 6.05 and 5.00 due to the left-digit anchoring effect. In seemingly unrelated research, it has been shown that incidental prices can affect buyers' valuation of goods and their willingness to pay. Specifically, Nunes and Boatwright (2004) found that the price of a sweatshirt on display at an adjacent seller can influence a shopper's willingness to pay for a music CD. Conceptualizing both these effects as manifestations of a common anchoring heuristic could facilitate the development of some generalizable principles of price cognition.

A caveat is due here. As some readers might have discerned by now, this chapter does not purport to be a comprehensive review of the behavioral pricing literature. Our primary objective is to explore whether focusing on the heuristics used in numerical cognition will bring forth some generalizable principles of price cognition. Further, we hope that this endeavor will contribute to the debate on awareness and intentionality (of biases) in price cognition. In the course of doing this, a review of the numerical cognition literature is necessitated because it provides us with the language (i.e. a typology of processes and representations) to delineate the mechanisms underlying these heuristics. Given this objective, this review will discuss only a few selected research studies in the behavioral pricing area that illustrate the use of anchoring, availability and representativeness in price magnitude judgments and judgments of the magnitude of a price difference. Readers interested in a more comprehensive review of the behavioral pricing literature are referred to Monroe and Lee (1999) for a numerical cognition perspective, Monroe (2003) and Raghubir (2006) for information-processing perspectives, and Winer (2006) for a managerial perspective on behavioral pricing.

Numerical cognition and pricing

An important question that has emerged as a dominant theme in the JDM literature, and of particular relevance to the issue of awareness and intentionality of biases, is whether heuristics are based on quick and associative processes (i.e. system 1) or slow and rule-based processes (i.e. system 2). As discussed by Kahneman and Frederick (2002), the influence of system 1 on judgments is believed to be less deliberate and more automatic than that of system 2. Characterizing the numerical cognition process as an interaction

of slow and rule-based, and fast and associative processes will be helpful in delineating the volitional and unintended elements of the heuristics used in numerical cognition. However, the meaning of 'quick and associative' in the context of numerical cognition is not clear. How can some numerical computations be faster and easier than others? Why are people unable to verbalize some aspects of numerical cognition processes? To understand more about associative processes in numerical cognition, we focus on two important findings in the numerical cognition literature in this review: (i) cognitive arithmetic is not always based on online computations; instead it involves associative knowledge structures stored in memory; and (ii) numbers can also be represented as analog magnitudes and processed non-verbally, in much the same manner as other analog stimuli such as light and sound are represented and processed.

Evidence for associative processes in cognitive arithmetic

The area of cognitive psychology that examines the mental representation and the cognitive processes that underlie responses to a math task is referred to as cognitive arithmetic. Although researchers in this area have traditionally focused on the study of addition and multiplication, we believe that in the context of price cognition, since consumers often consider differences in prices of comparable products, subtraction is perhaps the most ubiquitous arithmetic operation. Some of the findings reviewed below were initially studied in the context of addition and multiplication; however, subsequent research has revealed that they are relevant to subtraction (Zbrodoff and Logan, 2005).

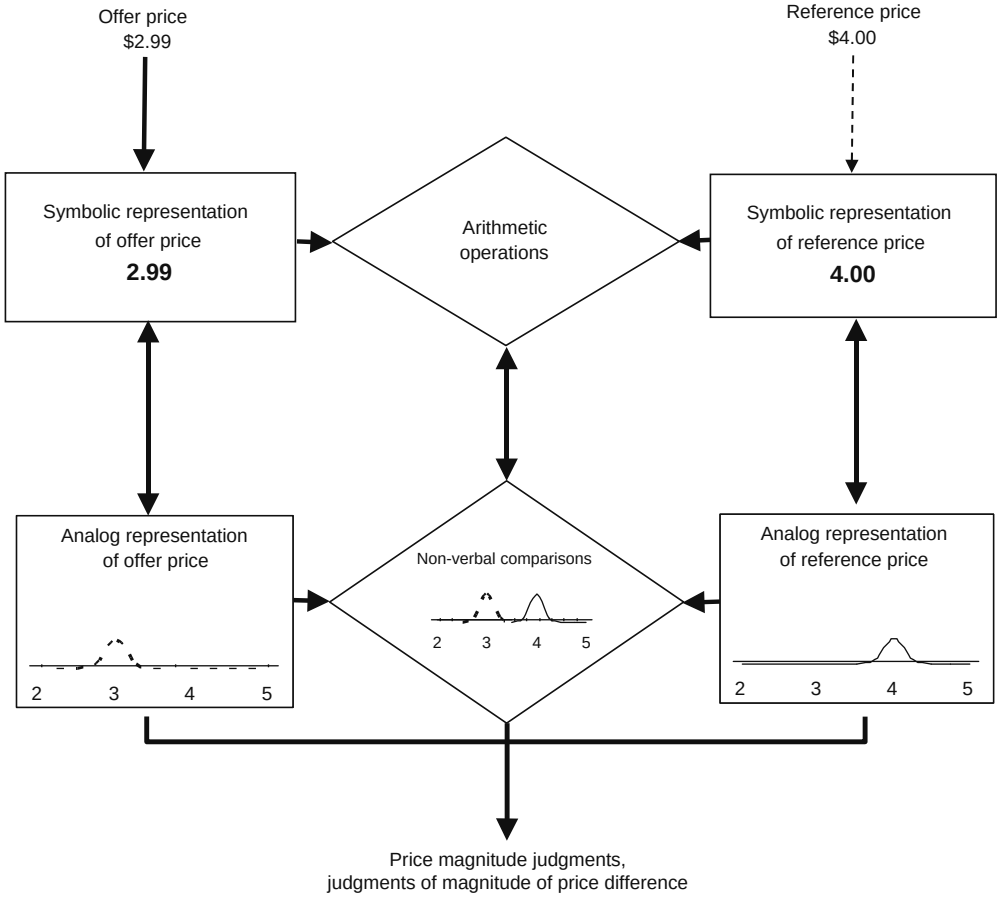
Ashcraft (1995) describes several pieces of evidence to suggest that responses to arithmetic problems are based not only on online computations but also on retrieval from associative knowledge structures. First, it has been shown that some problems can be solved faster than others. Problems that entail smaller numbers (e.g. $2 + 3$) are solved faster than problems that entail larger numbers (e.g. $7 + 9$); problems that include the number 5 are solved faster than problems that do not; and problems with identical operands (e.g. 8×8) are solved faster than other problems (e.g. 8×7). These patterns of response times for mental computations are comparable to the word frequency effects in language; they reflect the frequency with which arithmetic facts are acquired and practiced. Second, as in word recognition, repetition affects arithmetic fact retrieval: it is easier to respond to $7 + 9 = 16$ when it is presented the second time. Third, there is evidence for unintended interference in mental calculations by automatic activation of irrelevant arithmetic facts. For example, in a verification task, participants are less likely to respond 'false' to problems such as $3 + 4 = 12$ and $3 \times 4 = 7$ because the incorrect solutions to these problems are correct solutions to similar problems stored in the memory. This and other evidence reviewed by Ashcraft (1995) lead to an important conclusion about mental arithmetic: solutions to arithmetic problems are not always computed online; instead, mental arithmetic is based on associative knowledge structures in the memory.

The representation of arithmetic facts as associative knowledge structures has implications for price cognition processes. The spontaneous activation of arithmetic facts could influence consumers' judgments. For example, while computing the difference between \$4.00 and \$2.99, the left-digit difference ($4 - 2 = 2$) might spontaneously 'pop up' in the consumer's mind and might serve as an unintended anchor in numerical judgments. Such left-digit anchoring could cause consumers to incorrectly judge the difference between \$4.00 and \$2.99 to be larger than that between \$4.01 and \$3.00. Further, the spontaneous

activation of arithmetic facts makes some mental problems easier than others. For example, consumers will be able to assess the price difference between $500 and $400 much faster than that between $497 and $394. As we discuss later in this chapter, this ease by itself could influence consumers' price magnitude judgments.

Evidence for non-verbal processing of numbers

The arithmetic tasks discussed in the preceding section assume symbolic representations of numbers; the strings of digits in a multi-digit number are assumed to be represented in the working/long-term memory, preserving the syntactic structure of tens and units. However, magnitude judgments might not always entail such symbolic representations; instead they are assumed to entail analog representations. Analog representations refer to non-symbolic magnitude representations of the numbers on a subjective 'small–large'



Note: Price cognition is postulated to entail symbolic and analog representations. The arithmetic processes that operate on symbolic representations could be deliberative and rule-based or instinctive and associative. The non-verbal processes that operate on analog representations are likely to be instinctive and associative.

Figure 7.1 Putative processes in price cognition

mental number line (see Figure 7.1). In this section, we discuss the relevance of analog representations for price cognition.

When asked why she did not buy her usual brand of laundry detergent this week, a consumer might respond that her decision was based on the size of the difference between this week's price and the previous week's price. Such a response might mislead an observer to conclude that the numerical cognition process that led to this response might have entailed a symbolic comparison of two weekly prices: this week's price \$4.49 minus the previous week's price \$3.99 = 50 cents. While such a response could indeed be based on mental subtraction of symbolic representations, it is also possible that the response might have been based on the analog representations, in much the same way as she would judge the difference in hues of a light and a dark color, or the difference in the luminosity of a 30 watt bulb and a 60 watt bulb. Analog representations refer to semantic magnitude representations of the numbers on a subjective mental scale. Such analog representations are assumed to be similar to the representations of psychophysical stimuli such as light, sound, size etc. Dehaene (1992, p. 20) suggests that many of our daily numerical cognition tasks are based on analog judgments: 'tasks such as measurement, comparison of prices, or approximate calculations, solicit an approximate mode in which we access and manipulate a mental model of approximate quantities similar to a mental number line'.

Several pieces of evidence support the notion that numerical cognition entails analog representations. The most frequently cited evidence for the use of analog representations is the distance effect. In a typical distance effect experiment (e.g. Moyer and Landauer, 1967), pairs of digits such as 7 and 9 are flashed on the screen, and participants are asked to identify the higher digit by pressing one of two keys. The main finding from this experiment is that when the two digits stand for very different analog quantities such as 2 and 9, subjects respond quickly and accurately. But their response time slows down by more than 100 milliseconds when the two digits are numerically closer, such as 7 and 9. The distance effect has been interpreted by many cognitive psychologists as evidence for the proposition that magnitude judgments entail an internal analog scale. Dehaene suggests (p. 74):

> the brain does not stop at recognizing digit shapes. It rapidly recognizes that at the level of their quantitative meaning, digit 4 is indeed closer to 5 than 1 is. An analogical representation of the quantitative properties of Arabic numerals, which preserve the proximity relations between them, is hidden somewhere in the cerebral sulci and gyri. Whenever we see a digit, its quantitative representation is immediately retrieved and leads to greater confusion over nearby numbers.

The distance effect manifests even when the comparison standard is not shown on the screen. For example, Dehaene et al. (1990) flashed randomly selected numbers between 31 and 99 on the screen, one at a time, and asked participants to judge whether the shown number was lower or higher than 65. That the distance effect has been shown to occur with all sorts of psychophysical stimuli such as light, sound, size etc. suggests that numbers also can be processed as psychophysical stimuli.

Additional support for the existence of analog representations of numbers comes from the fact that numerical cognition is non-verbal: it does not require linguistic capabilities. Infants and animals can also comprehend magnitude information. Based on the differences in the time that infants take to look at displays with different numbers of dots, Starkey and Cooper (1980) suggest that four- to seven-month-old infants can discriminate

between quantities of two and three. Similar results were presented by Lipton and Spelke (2003). Gallistel and Gelman (2005) found that the distance effect manifests in animals. This observation, once again, implies that linguistic ability is not necessary for representing the magnitude information. Based on such findings, Gallistel and Gelman (2005, p. 559) suggest that the human ability to think mathematically might draw on a primitive, non-verbal system: 'the verbal expression of number and of arithmetic thinking is based on a non-verbal system for estimating and reasoning about discrete and continuous quantity, which we share with many non-verbal animals'.

Researchers have also found evidence for the association of spatial orientation and numerical information. Several studies have shown that people's spatial orientation affects their ability to make magnitude judgments, a result known as the SNARC (spatial–numerical association of response codes) effect. Dehaene et al. (1993) showed participants in their experiment numbers between 0 and 9, one at a time, on a computer screen and asked them to judge whether the shown number is odd or even (i.e. parity). The assignment of the 'odd' and 'even' responses to response keys was varied within subjects such that for each number, participants responded using the left key in one half of the experiment and the right key in the other half. Results showed that, regardless of the parity, larger numbers yielded faster responses with the right hand than with the left, and the reverse was true for smaller numbers. The large–right and small–left associations are consistent with the notion that numbers are represented non-verbally. These spatial magnitude associations suggest that numbers activate semantic magnitude representations on a horizontal number line that extends from left to right, with smaller numbers on its left and larger numbers on its right.

The representation of numbers as analog representations raises new challenges as well as opportunities for theories of price cognition. An inevitable question that surfaces from this discussion is: when are prices likely to be represented and processed as analog representations or as symbolic representations? There is some evidence to suggest that price magnitude judgments are influenced by both analog and symbolic representations. Left-digit anchoring could be considered a signature of symbolic processing. If consumers were to ignore the numerical symbols and focus only on the underlying magnitudes, then they should perceive the difference between \$4.00 and \$2.99 to be the same as that between \$4.01 and \$3.00. The abundant evidence for left-digit anchoring (Schindler and Kirby, 1997; Stiving and Winer, 1997; Thomas and Morwitz, 2005) suggests that price cognition does entail symbolic processing. However, some studies have also found evidence for the distance effect in price magnitude judgments (Thomas and Morwitz, 2005, experiment 3; but see Viswanathan and Narayan, 1994), which is a signature of analog processing. Further, Thomas and Menon (2007) found that phenomenological experiences can affect consumers' price magnitude judgments even when the articulated price expectation remains unchanged. They interpreted this evidence as suggesting that while price magnitude judgments entail analog representations of reference prices, articulated price expectations draw on symbolic representations of prices in memory. Such a distinction between analog and symbolic representations of prices offers a promising framework to address a long-standing conundrum in the pricing literature: consumers are not very good at recalling the past prices of products (Dickson and Sawyer, 1990; Gabor, 1988; Urbany and Dickson, 1991), yet their brand choices are very sensitive to small changes in prices relative to past prices (Kalyanaram and Winer, 1995; Winer, 1988; also see Monroe and Lee, 1999). Exploring the dissociation between analog and symbolic representations

of price knowledge, understanding when one representation is likely to be more influential than the other, and examining how these two distinct types of price knowledge interact with each other could be promising avenues for future research.

A putative model of price cognition

The literature reviewed in the preceding paragraphs suggests that price magnitude judgments might be based on symbolic representations, analog representations, or on a combination of the two (see Figure 7.1). The processes that operate on these representations can be grouped into two distinct families: they can either be deliberative and rule-based or instinctive and associative. The non-verbal processes that operate on analog representations are likely to be instinctive and associative. For example, although we can easily identify the more luminous bulb when presented with two lighted bulbs of differing luminosities, it is difficult to explain how we made the judgment. In a similar vein, when people judge the magnitudes of two numbers using analog representations, they are likely to be aware of the final judgment without knowing how they arrived at it. However, the arithmetic processes that operate on symbolic representations could either be deliberative and rule-based or instinctive and associative. Specifically, they are likely to be deliberative and rule-based when people have to do online computations to respond to an arithmetic problem, but they are likely to be instinctive and associative when the response can be retrieved from associative knowledge structures in the long-term memory. People might have introspective access to the deliberative and rule-based cognitive processes, and therefore might be able to report the cognitive strategies used in such processes.

Figure 7.1 adapts Dehaene's (1992; also discussed in McCloskey and Macaruso, 1995) framework of numerical comparison to represent the putative processes in price magnitude judgments. These processes are best illustrated by an example. Consider a consumer who is evaluating a stimulus price, $2.99. Numerical judgments usually involve comparisons with a reference point (Thomas and Menon, 2007; Winer, 1988). The broken line connecting the reference price to its internal representation indicates that it could either be retrieved from memory (an internal reference price), or it could be the most relevant comparison standard at the point of sale (an external reference price). During the encoding stage, the numerical symbols are transcoded to an analog representation in consumers' working memory. As discussed in the preceding paragraphs, the three digits in the numerical stimulus (2, 9 and 9) could be represented holistically as a discriminal dispersion on the psychological continuum used to represent magnitudes (see Figure 7.1). Also activated on the mental number line is the analog representation of the comparison standard associated with the stimulus product. The final response toward the stimulus price could be based on arithmetic operations on the symbolic representations, non-verbal comparisons of analog representations, or on a combination of these processes.

Heuristics in price cognition

Having characterized the representations and processes that underlie the price cognition process, we now review some of the heuristics used in price magnitude judgments and judgments of the magnitudes of price differences. Specifically, we focus on three heuristics: anchoring, representativeness and availability.

Anchoring in price cognition

The anchoring effect, which was first demonstrated in the context of numeric estimates, refers to the influence of uninformative or irrelevant numbers in numerical cognition. In their classic study, Tversky and Kahneman (1974) asked participants to estimate the percentage of African nations in the UN. Before they indicated their response, participants were first asked to indicate whether their estimate was higher or lower than a random number between 0 percent and 100 percent generated by spinning a wheel of fortune. These arbitrary numbers had a significant effect on participants' estimates. For example, participants who were first asked 'Was it more or less than 45 percent?' guessed lower values than those who had been asked if it was more or less than 65 percent. Since the publication of these results, several studies have documented the effect of anchoring in the context of price cognition (Adaval and Monroe, 2002; Bolton et al., 2003; Morwitz et al., 1998; Chapman and Johnson, 1999; Mussweiler and Englich, 2003; Northcraft and Neale, 1987; Raghubir and Srivastava, 2002; Schkade and Johnson, 1989; Thomas and Morwitz, 2005).

Mussweiler and Englich (2003) found that anchoring effects are more likely when people use an unfamiliar currency than a familiar currency. The introduction of the euro as a new currency in Germany offered them a natural setting to test the moderating role of currency familiarity in anchoring effects. Participants in their experiment were asked to estimate the price of a mid-sized car, immediately before and about half a year after the introduction of the euro. The researchers found that immediately before the introduction of the euro, the anchoring bias was more likely to manifest when German participants made price estimates in euros than in German marks. However, six months after the introduction of the euro, this pattern was completed reversed: euro estimates were less biased than mark estimates. Similar results were reported by Raghubir and Srivastava (2002). In a series of experimental studies, they found that people's valuation of a product in an unfamiliar foreign currency is anchored on its face value, with inadequate adjustment for the exchange rate. As a consequence, an American consumer is likely to underspend in Malaysia (because 1 US dollar = 4 Malaysian ringgits) and overspend in Bahrain (because 1 US dollar = 0.4 Bahraini dinar). As in Mussweiler and Englich's research, familiarity with the foreign currency was found to be a moderator of the face value anchoring effect. Morwitz et al. (1998) demonstrated anchoring effects in the context of partitioned prices. They found that charging the shipping and handling fee as a separate component from the catalog price reduced recall of total cost because of the propensity to anchor on the base price. In another experiment, Morwitz et al. (1998) found that auction bidders agreed to pay more in total cost in an auction when a 15 percent buyer's premium was charged separately than in one in which there was no buyer's premium. The anchoring effect observed in partitioned pricing has subsequently been replicated and extended in several studies (e.g. Bertini and Wathieu, 2008; Chakravarti et al., 2002).

Although these studies demonstrate the pervasiveness of the anchoring heuristic in price cognition, it is not clear whether the observed anchoring effects are the results of volitional cognitive strategies, or a consequence of the associative and non-verbal processes in price cognition. Some studies have explicitly addressed the issue of awareness and intentionality in anchoring.

Unaware anchoring Northcraft and Neale (1987) examined the effect of the anchoring heuristic in price estimates in an information-rich, real-world setting. They asked

students and real-estate agents to tour a house and appraise it. Their results revealed that not only the students' but also the real-estate agents' price estimates were anchored on the list price of the house. It could be argued that the use of an anchoring strategy in this example is not completely unwarranted. Since list prices are usually correlated with the real-estate value, participants in this experiment might have considered list price as relevant information. However, analysis of the decision processes based on participants' verbal protocols revealed that the real-estate agents seemed to be unaware of the anchoring effect of the list price: a majority of them flatly denied that they considered the list price while appraising the property.

Unintentional anchoring The proposition that anchoring might be occurring unintentionally is supported by the finding that completely irrelevant anchors can also affect people's price estimates and magnitude judgments. Nunes and Boatwright (2004) suggest that incidental prices (i.e. prices advertised, offered or paid for unrelated goods that neither sellers nor buyers regard as relevant to the price of an item that they are engaged in buying) can affect buyers' valuation of goods and their willingness to pay. They find that the price of a sweatshirt on display at an adjacent seller can influence a shopper's willingness to pay for a music CD. Adaval and Monroe (2002) show that even subliminally primed numbers can affect consumers' price magnitude judgments. The researchers demonstrate that exposing subjects to high numbers below the consumer's threshold of perception can make the price of a product seen later seem less expensive. This effect manifests even when the subliminal information is completely irrelevant (e.g. weight in grams) to the price judgment task. Their results suggest that numerical information is translated into a magnitude representation regardless of the associated attribute dimension (e.g. grams or dollars).

Another example of unintentional anchoring in price cognition is the left-digit effect in judgments of the magnitude of price differences. Research has revealed that the propensity to read from left to right leads to anchoring in judgments of the magnitude of the numerical difference. Thomas and Morwitz (2005) demonstrated that using a 9-ending price can affect judgments of the magnitude of the difference between two prices when the use of such an ending leads to a change in the left-most digit (e.g. $3.00 versus $2.99), but has no effect on the perceived magnitude when the left-most digit remains unchanged (e.g. $3.50 versus $3.49). More recently, these researchers found that participants in an experiment judged the numerical difference to be larger when the left-digit difference is larger (e.g. 6.00 minus 4.95) than when the left-digit difference is smaller (e.g. 6.05 minus 5.00), even though the holistic differences are identical across the pairs. Evidence for the left-digit effect has also come from analyses of scanner panel data (Stiving and Winer, 1997) and a survey of retailers' pricing practices (Schindler and Kirby, 1997).

Cognitive miserliness or numeric priming? Economists and like-minded marketing researchers have suggested that such left-digit anchoring in judgments is on account of volitional cognitive miserliness. This stream of literature suggests that the left-digit effect occurs because consumers volitionally ignore the right digits. Characterizing a model of rational consumer behavior, Basu (2006, p. 125) suggested that consumers do not ignore the right digits 'reflexively or out of irrationality, but only when they expect the time cost of acquiring full cognizance of the exact price to exceed the expected loss caused by the

slightly erroneous amount that is likely to be purchased or the slightly higher price that may be paid by virtue of ignoring the information concerning the last digits of prices'. In a similar vein, Stiving and Winer (1997, p. 65) suggest that consumers ignore the pennies digits in a price because they might be 'trading off the low likelihood of making a mistake against the cost of mentally processing the pennies digits'.

However, the price cognition model described earlier in this review suggests that the left-digit effect can manifest even when consumers diligently compute holistic numerical differences. Mental subtraction of multi-digit numbers proceeds from left to right, and entails several intermediate steps. One such step is the retrieval/computation of the difference between left-most digits as an initial anchor. For example, when a consumer tries to compute the holistic difference between $6.00 and $4.95, the difference between the left-most digits 6 and 4 might 'pop up' in her mind. Thus the left-digit difference is activated in the consumer's working memory as an intermediate step. Even when the consumer corrects this intermediate output for the right digits, the activation of this left-digit difference in working memory can unobtrusively prime the consumer's judgments. Thus the subjective numerical judgment is affected not only by the final corrected output (i.e. 1.05) but is also contaminated by the initial anchor (i.e. 2) generated during the mental subtraction process. This example illustrates the divergence in the predictions from the traditional economic models based on assumptions of deliberative and controlled thinking, and the price cognition model characterized by associative and non-verbal processes.

In conclusion, the evidence reviewed in this section supports the proposition that consumers' responses to prices are often influenced by irrelevant anchors. Further, in many instances, this influence seems to be occurring unintentionally and without consumers' awareness.

Representativeness heuristic in price cognition

According to Gilovich and Savitsky (2002, p. 618), the representativeness heuristic refers to the 'reflexive tendency to assess the fit or similarity of objects and events along salient dimensions and to organize them on the basis of one overarching rule: Like goes with like.' The classic engineer–lawyer study, discussed by Tversky and Kahneman (1974), offers an excellent illustration of the use of representativeness heuristic in everyday judgments. Participants in their experiment were provided with the non-diagnostic descriptions of several individuals, such as:

> Dick is a 30 year old man. He is married with no children. A man of high ability and high motivation, he promises to be quite successful in his field. He is well liked by his colleagues.

Further, the participants were informed that the described individuals were sampled at random from a group of 100 professionals – engineers and lawyers. Half the participants were told that this group consisted of 70 engineers and 30 lawyers, while the other half were told that the group comprised 30 engineers and 70 lawyers. Tversky and Kahneman (1974) found, as they predicted, that the base rate manipulation had little effect on participants' judgment of the probability of Dick being an engineer. The results suggest that participants in the experiment might have judged the probability based on the degree to which the description was representative of the two stereotypes, without considering the base rates for the two categories.

Although in this experiment participants relied only on the representativeness heuristic and ignored rule-based reasoning, as Kahneman and Frederick (2002) suggest, this may not always be the case. In many instances, rule-based reasoning and heuristic thinking can co-occur.[3] In our view, it is almost impossible to ignore rule-based thinking while evaluating numeric information such as price. The effects of representativeness-based thinking are likely to surreptitiously influence judgments as consumers engage in systematic rule-based evaluation of prices, so their final magnitude judgments are likely to be conjointly influenced by rule-based and representativeness-based thinking.

Representativeness of font size Although the use of the representativeness heuristic has not been specifically implicated in price cognition, some published results could be reinterpreted as evidence for the use of representativeness. In our view, the size congruity effect reported by Coulter and Coulter (2005) is a good example of the influence of the representativeness heuristic in price cognition. Coulter and Coulter's (2005) results indicate that price magnitude judgments are not only influenced by the magnitude of the price but also by the physical size of the symbolic representation. The researchers predicted that consumers are likely to perceive an offered price to be lower when the price is represented in smaller than in larger font. To test this hypothesis, they presented participants with an advertisement for a fictitious brand of an in-line skate sold on sale; in addition to the usual product details, the advertisement also displayed the regular ($239.99) and the sale prices ($199.99) for the product. For half the participants, the font used for the sale price was smaller than that used for the regular price ($239.99 versus $199.99). For the other half, the font used for the sale price was larger ($239.99 versus $199.99). The results revealed that participants' evaluations of the sale price magnitude and their purchase intentions were influenced by this font manipulation. Participants judged the sale price magnitude to be lower when the font size for the sale price was smaller. Interestingly, participants' self-reports of their decision-making processes revealed that the effect occurred nonconsciously: they could not recall details of the font size manipulation, and a majority reported that font size did not influence their judgments at all. These results suggest that participants might have nonconsciously inferred smaller font size to be representative of lower price magnitudes.

Representativeness of digit patterns Consumers might also rely on representativeness of digit patterns to make magnitude judgments. Thomas et al. (2007) examine whether precision or roundedness of prices affects consumers' magnitude judgments. They found that consumers incorrectly perceive precise prices ($395 425) to be lower than round prices (e.g. $395 000) of similar magnitude. Previous research on the distribution of numbers has shown that all numbers do not occur with uniform frequency in printed or spoken communication. Dehaene and Mehler (1992) analyzed the frequency of number words in word frequency tables for English, Catalan, Dutch, French, Japanese, Kannada and Spanish languages. They found an overrepresentation of small, precise numbers (e.g. 1, 2, 3, . . ., 8 and 9) and large numbers rounded to the nearest multiple of 10 (e.g. 10, 20, . . ., 100, 110). Stated differently, precise large numbers (e.g. 101, 102, 103, . . .,1011, 1121)

[3] See Gilbert (1999) for a discussion on consolidative and competitive models of dual process systems.

are used relatively infrequently in our daily communication. This finding was replicated in studies on the patterns of number usage in the World Wide Web and in newspapers. Given this evidence of greater prevalence of precision in smaller numbers and roundedness in larger numbers, Thomas et al. (2007) hypothesized that the representativeness of digit patterns might influence judgments of magnitude. Specifically, drawing on previous research on the distribution of numbers and on the role of representativeness in everyday judgments, they suggest that people nonconsciously learn to associate precise prices with smaller magnitudes. They tested this hypothesized precision heuristic in a laboratory experiment. Participants in their experiment were asked to evaluate 12 different list prices of a house listed for sale in a neighboring city. Six of these prices were precise and the other six round. Participants were randomly assigned to two groups and each group evaluated six of the 12 prices, one at a time, in a random order on computer screens. Specifically, one of the groups evaluated the prices $390 000, $395 000, $400 000, $501 298, $505 425 and $511 534, while the other group evaluated $391 534, $395 425, $401 298, $500 000, $505 000 and $510 000. Consistent with their prediction, the researchers found that participants, systematically but incorrectly, judged the magnitudes of the precise prices to be significantly smaller than the round prices. This result suggests that magnitude judgments are influenced by the representativeness of digit patterns: precise digit patterns are considered to be representative of smaller magnitudes.

In conclusion, the evidence reviewed in this section suggests that price magnitude judgments can be influenced by representativeness-based thinking. The research we reviewed suggests a reflexive tendency in consumers to assess the magnitude of a price based on irrelevant factors such as font size and digit patterns. Given the obvious irrelevance of these factors, it is unlikely that consumers might be relying on these factors intentionally. It seems reasonable to assume that representativeness-based thinking might be influencing price magnitude judgments unintentionally and without consumers' awareness.

Availability heuristic in price cognition

People rely on the ease or the fluency with which information is processed to make judgments, a decision rule referred to as the availability heuristic. To demonstrate the role of the availability heuristic in judgments, Tversky and Kahneman (1974) asked participants whether it is more likely that a word begins with *r* or that *r* is the third letter in a word. Because words that begin with *r* come to mind faster than words with *r* as the third letter, participants overestimated the number of words that begin with *r*, and underestimated the words that have *r* as the third letter. Note that this effect in judgments could have occurred through two distinct mechanisms: (i) participants might have experienced a feeling of ease while retrieving words that begins with *r*, and might have made inferences based on this experiential information; or (ii) they might have been able to recall more words that start with *r*. In the former case, the judgment would be based on experiential information, while in the latter case it would be based on declarative information. Subsequent research (see Schwarz et al., 1991) revealed that experiential information by itself can influence judgments: the perceived ease or difficulty of information-processing influences judgments even when the declarative information is inconsistent with the experiential information.

Meanwhile, independent of this stream of research in judgment and decision-making, social and cognitive psychologists have discovered that fluency or ease of processing has

remarkable effects on preferences (Zajonc, 1980) and implicit memory (Jacoby et al., 1989). More recent research has identified that different types of fluency – conceptual and perceptual – have distinct effects on judgments (Whittlesea, 1993). These findings have had a substantive impact on research on consumer behavior: researchers have demonstrated that information processing fluency can influence judgments on a range of evaluative dimensions. However, although researchers examining consumer behavior have found that processing fluency can affect evaluations of products (e.g. Janiszewski, 1993; Lee and Labroo, 2004; Menon and Raghubir, 2003), it could be argued that not much work has been done to explore the consequences of processing fluency in the domain of pricing. In this review, we discuss some fluency effects that could be relevant to the understanding of price cognition process. Specifically, we discuss the effects of fluency on willingness to pay (Alter and Oppenheimer, 2006; Mishra et al., 2006) and on judgments of the magnitude of numerical differences (Thomas and Morwitz, forthcoming).

Fluency and willingness to pay Alter and Oppenheimer (2006) suggest that information-processing fluency can affect the price that investors and traders are willing to pay for shares listed on the stock market. They found empirical support for their suggestion in laboratory studies as well in real-world stock market data. In a laboratory experiment, they asked one group of participants to rate a list of fabricated stocks on the ease of pronunciation, as a proxy for fluency. A second group of participants estimated the future performance of the fabricated stocks. As predicted, participants expected more fluently named stocks to outperform the less fluently named stocks. For example, participants predicted that shares of the firm named Yoalumnix (a less fluent name) will depreciate by 11 percent while the shares of Barnings (a fluent name) will appreciate by 12 percent. In a subsequent study, the researchers found similar effects in real-world stock market data: actual performance of shares with easily pronounceable ticker codes were better than those of shares with unpronounceable ticker codes in the short run.

Mishra et al. (2006) suggest that fluency can also influence people's preference for certain denominations of money. Their findings suggest that consumers find processing money in smaller denominations (e.g. five $20 bills) less fluent that processing money in larger denominations (e.g. one $100 bill). The hedonic marking created by such fluency experiences results in a lower inclination to spend money when it is in larger denominations. Together, these studies suggest that fluency experiences can, in a variety of ways, affect buyers' valuations and willingness to pay for goods.

The ease of computation effect Thomas and Morwitz (forthcoming) suggest that the feelings of ease or difficulty induced by the complexity of arithmetic computations systematically affect people's judgments of numerical differences. Usually, the closer the representations of two stimuli on the internal analog scale, the greater the processing difficulty. It is easier to discriminate between two bulbs of 30 and 120 watts of power than to discriminate between bulbs of 70 and 80 watts of power. Likewise, it is more difficult to discriminate between two weights or two sound pitches that are similar to each other than two that are relatively far apart. However, overuse of this ease of processing heuristic can lead to biases in judgments of numerical differences. When presented with two pairs of prices with similar magnitudes of arithmetic difference, participants in Thomas and Morwitz's experiments incorrectly judged the difference to be smaller for pairs with

difficult computations (e.g. 4.97–3.96; arithmetic difference 1.01) than for pairs with easy computations (e.g. 5.00–4.00; arithmetic difference 1.00). They show that this ease of computation effect can influence judgments of price differences in several contexts. Ease of computation can influence the perceived price difference between competing products, and can also affect the perceived magnitude of a discount (i.e. the difference between regular and sale prices). Interestingly, they observed that the ease of computation effect is mitigated when participants are made aware that their experiences of ease or difficulty are caused by computational complexity. This finding suggests that the ease of computation effect is unlikely to be due to hedonic marking, and might be due to the nonconscious misattribution of metacognitive experiences.

In conclusion, the evidence we have reviewed suggests that consumers' willingness to pay and judgments of price differences could be influenced by the ease of information-processing. Ease of information-processing can be influenced by several incidental factors such as how easy or difficult it is to pronounce the name of the product, or whether money is held in small or large denominations. The ease of computation effect in judgments of numerical differences reveals that the fluency of information-processing not only influenced affective responses to stimuli, but also influenced cognitive judgments. The empirical regularities we have reviewed are quite counterintuitive. Clearly, no buyer will knowingly invest in a company on the basis of the fluency of its name, or be less willing to spend because of the denominations of wealth. Similarly, people will not knowingly judge that the difference between 4.97 and 3.96 is smaller than that between 5.00 and 4.00. The glaring normative inappropriateness of these judgments suggests that people might be unaware of these fluency effects in their price cognition, and therefore these effects might be occurring unintentionally.

Conclusion

Our objective in this chapter was to examine the psychological mechanisms that underlie the price cognition process. We chose to organize this review around the issues of awareness and intentionality in price cognition. The choice of these issues as the focal theme should not be interpreted as suggesting that all of price cognition occurs without awareness or intention. Demonstrating that the price cognition process is susceptible to unaware and unintended influences is one way to persuade a circumspect reader that price evaluations are not always based on economically valid rule-based reasoning, as portrayed in several models of consumer behavior.

We reviewed two distinct sets of literature to marshal evidence for our proposition that price cognition might entail processes that are not available to introspective analyses. The numerical cognition literature suggests that mental arithmetic relies not only on online computations, but also on activation of patterns of associations stored in the memory. Further, this literature also offers evidence for the existence of a non-verbal numerical cognition system: we can make numerical judgments based on analog representations in much the same way that we judge psychophysical stimuli such as light and sound. Then, drawing on the judgment and decision-making literature, we characterized the heuristics that people use to make price estimates, price magnitude judgments, and judgments of the magnitude of price differences. We showed that people rely on anchoring, availability and representativeness in price cognition, much as they do for other everyday judgments. Relying on the anchoring heuristic makes people incorrectly judge the difference between

6.01 and 5.00 to be smaller than that between 6.00 and 4.99; relying on the representativeness heuristic makes people incorrectly judge $391 534 to be lower than $390 000; relying on the availability heuristic makes people incorrectly judge the difference between 4.97 and 3.96 to be smaller than that between 5.00 and 4.00.

A circumspect reader could argue that the behavioral pricing effects reviewed in this chapter are anomalous deviations that do not represent the usual price cognition processes. Indeed, as we suggested earlier, we do not consider rule-based reasoning and heuristic evaluations of prices as mutually exclusive processes; heuristic processes can co-occur, and sometimes interact, with rule-based thinking. Further, we also acknowledge that rule-based reasoning could account for much of the variance in consumers' responses to prices. However, we believe that delineating the representations and processes that underlie consumers' responses to prices will have substantive and theoretic implications. First, this stream of research can lead to a sound theoretical basis for formulating a price digit policy. The findings in this stream of research highlight that pricing decisions entail more than just deciding the magnitude of the optimal price; managers also have to decide what type of digits to use for the optimal price magnitude. For example, if consumer research and strategic analysis reveals that the optimal price magnitude for a product is $4.50, then the manager is left with the task of deciding whether the final price should have a 9-ending (i.e. $4.49) or whether it should have precise digits (e.g. $4.53) or some other pattern of digits (e.g. $4.44). There is empirical evidence that such decisions can have a significant impact on sales and profits (Anderson and Simester, 2003; Schindler and Kibarian, 1996; Stiving and Winer, 1997). Second, understanding how prices are represented and processed can address the conundrum of how consumers seem to 'know' the prices without being able to recall them (Dickson and Sawyer, 1990; Monroe and Lee, 1999). Finally, this stream of research also promises to augment the pricing literature by providing a unifying framework to discuss the many seemingly unrelated effects reported in the literature.

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8 Price cues and customer price knowledge

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Abstract

A price cue is defined as any marketing tactic used to persuade customers that prices offer good value compared to competitors' prices, past prices or future prices. In this chapter, we review the academic literature that documents the effectiveness of different types of prices cues. The leading economic explanation for why price cues are effective focuses on the role of customer price knowledge and the ability of customers to evaluate whether prices offer good value. We survey the evidence supporting this theory, including a review of the literature on customer price knowledge. Finally, we document the boundaries of when price cues are effective and identify several moderating factors.

Introduction

What is a good price to pay for a 16 ounce package of baking soda? Is $2599 a good price for a 40″ flat-panel television? Classical economic theory assumes that customers have perfect information and can accurately answer such questions. Yet many customers who walk into Best Buy and see a 40″ television priced at $2599 are unsure of both what price Circuit City charges, or whether Best Buy will lower the price in coming weeks. This lack of information provides an opportunity for retailers to influence consumers' price perceptions through the use of 'price cues'.

We broadly define a price cue as any marketing tactic used by a firm to create the perception that its current price offers good value compared to competitors' prices, past prices or future prices (Anderson and Simester, 2003b). A common example is placing a sign at the point of purchase claiming an item is on 'Sale'. However, the definition is broad enough to also include more subtle techniques such as $9 price endings, price-matching guarantees, employee discount promotions and low advertised prices.

Our review of the existing academic research on price cues will focus on seven key results:

1. Many customers have poor price knowledge.
2. Price cues are effective at increasing demand.
3. Price cues are more effective (and actual price changes are less effective) when customers have poor price knowledge.
4. Price cues are most effective on newly introduced items and with newly acquired customers.
5. Price cues are less effective when used more often.
6. It is profitable for firms to place price cues on items for which prices are low.
7. Price cues may lower demand if used incorrectly

The evidence for these results is summarized in Box 8.1. Though not apparent from this summary, this body of research is notable for the range of product categories studied, extending from employee discount promotions for new automobiles to price-matching

BOX 8.1 KEY RESEARCH FINDINGS

1. Many customers have poor price knowledge.
See Monroe and Lee (1999) for a review of 16 studies. Subsequent research includes Vanhuele and Drèze (2002).

2. Price cues are effective at increasing demand.
'Sale' or 'low price' merchandising claims: Guadagni and Little (1983); Inman et al. (1990); Inman and McAlister (1993); Davis et al. (1992); Anderson and Simester (1998 and 2001a); Anderson et al. (2008).

Employee discount promotions: Busse et al. (2007), who study the impact of the 2005 employee discount promotions in the automobile industry.

Price-matching guarantees: Jain and Srivastava (2000), who present evidence that price-matching claims lead to favorable price perceptions.

9-digit price endings: Schindler and Warren (1988); Schindler (1991); Salmon and Ortmeyer (1992); Stiving and Winer (1997); Anderson and Simester (2003a); and Schindler (2006).

Initial prices: Bagwell (1987) presents an equilibrium model, while Anderson and Simester (2004) compare the long-run impact of offering deep discounts to existing and newly acquired customers.

Prices of 'signpost items' (for which customers have good price knowledge): Simester (1995) presents both an equilibrium model and data from the Boston dry-cleaning market.

Prices of related items: Anderson and Simester (2007a and 2007b). See also Xia et al.'s (2004) review of the extensive literature on price fairness and Kalyanaram and Winer's (1995) review of the reference price literature.

3. Price cues are more effective and actual price changes are less effective when customers have poor price knowledge.
Anderson and Simester (1998) present a theoretical model, while Anderson et al. (2008) present empirical evidence from a chain of convenience stores.

4. Price cues are most effective on newly introduced items and with newly acquired customers.
Anderson and Simester (2003a) show that 9-digit price endings are most effective on new items, while Anderson and Simester (2004) present evidence that low initial prices are most effective on new customers.

5. Price cues are less effective when used more often.
This is a central prediction in the Anderson and Simester (1998) model, and is tested empirically in Anderson and Simester (2001a) using data from a variety of sources.

6. It is profitable for firms to place price cues on items for which prices are low.

This is also a central prediction in the Anderson and Simester (1998) model. For a recent empirical investigation of this issue see Anderson et al. (2008).

7. Price cues may lower demand if used incorrectly.

Including the regular price (when customers expect a larger discount): see the results cited in this chapter.

When quality is uncertain: Anderson and Simester (2001b) show that installment billing offers can lower demand.

When prices of related items reveal that other customers pay lower prices: see Anderson and Simester (2007a and 2007b) and Xia et al.'s (2004) review.

guarantees for supermarkets. We begin our discussion by reviewing the literature on customer price knowledge. We then discuss both the effectiveness of price cues and theories that explain why consumers are so responsive to them.

Price knowledge

There has been considerable research investigating customer price knowledge. Monroe and Lee (1999) cite over 16 previous studies, most of which focus on measuring customers' short-term price knowledge of consumer packaged goods. In a typical study, customers are interviewed either at the point of purchase or in their home and asked to recall the price of a product, or alternatively, to recall the price they last paid for an item. In one of the earliest studies, Gabor and Granger (1961) conducted in-home interviews with hundreds of housewives in Nottingham, England. They found that consumers were able to provide price estimates for 82 percent of the products in their study. Thus, 18 percent of customers were not able to recall the price of an item. In addition, only 65 percent of customers were able to recall a price within 5 percent of the actual price. These findings have been replicated in later studies, which generally reveal that only half of the customers asked can accurately recall prices (Allen et al., 1976; Conover, 1986; *Progressive Grocer*, 1964, 1975). In perhaps the most frequently cited study, Dickson and Sawyer (1990) asked supermarket shoppers to recall the price of an item shortly after they placed it into their shopping cart. Surprisingly, fewer than 50 percent of consumers accurately recalled the price. Thus, despite the immediate recency of the purchase decision, there is no improvement in the accuracy of the responses.

While price recall taps into consumers' explicit memory, recent research has suggested that consumers may encode and store price knowledge in implicit memory. Monroe and Lee (1999) argue that this implies a clear distinction between what consumers remember about prices versus what they know about prices. They remark that 'the distinction between remembering and knowing contrasts the capacity for conscious recollection about the occurrence of facts and events versus the capacity for non-conscious retrieval of the past event, as in priming, skill learning, habit formation, and classical conditioning' (p. 214). This research suggests that price recall measures do not account for price information stored in consumers' implicit memory.

Building on this research, Vanhuele and Drèze (2002) argue that customers' long-term knowledge of prices is more accurately captured by measuring consumer price recognition and deal recognition. They survey 400 shoppers in a French hypermarket as they arrived at the store. Consistent with past research, they find that consumers have very poor price recall as only 21 percent of customers are within 5 percent of the actual store price. While consumers have poor price recall, the authors also show that they have significantly greater price recognition.[1] This supports the belief that multiple measures may be required to capture all aspects of customer price knowledge.

While Vanhuele and Drèze's (2002) work provides convincing evidence that price recall and price recognition are different constructs, it also leaves several unanswered questions. For example, we do not know the determinants of price recognition or which of these determinants are different from that of price recall. Moreover, the distinction between price recall and price recognition has received only limited attention in the price cue literature. As we shall discuss, the leading economic explanation for the effectiveness of price cues depends critically on lack of customer price knowledge. However, this theory does not distinguish between the inability of customers to recall prices and their inability to recognize them.

We now turn to the price cue literature, starting with the early work measuring whether price cues are effective.

Effectiveness of price cues

Academic research has now documented that price cues can have a large positive impact on demand. For example Inman et al. (1990) simulate a grocery shopping environment and find that price cues significantly increase demand. In one of the first papers to employ scanner data, Guadagni and Little (1983) find that the impact of a price cue (a display or feature) is an order of magnitude greater than price. Subsequent studies of scanner data have replicated this effect and find large, positive effects of in-store features and displays on consumer choice.

One challenge to empirically estimating the effect of a price cue is that price discounts often vary with price cues. Field studies have been used to isolate the impact of a price cue from a change in price. Inman and McAlister (1993) conduct a series of price experiments in a grocery store located on the campus of a major university. In nine categories they find that price cues can increase profits by 10 percent relative to using only price discounts. Anderson and Simester (2001a) report on a number of field tests conducted with direct mail retailers in which they vary price cues. In these experiments, consumers are randomly assigned to a condition and receive different versions of a retail catalog. The catalogs are identical except for the experimental variation in prices or price cues. They repeatedly find large positive effects; for example, demand for a dress increased by 58 percent when a dress includes a 'Sale' sign.

Perhaps surprisingly, the evidence that 'Sale' signs are effective extends beyond consumer packaged goods to include purchases of expensive durable goods. Busse et al. (2007) investigate the 'employee pricing' promotions offered by the three major US

[1] The authors measure aided price recognition as the ability of a consumer to tell whether an observed price is the one 'they have in mind' or 'are used to seeing' (see Monroe et al., 1986).

domestic automobile manufacturers during the summer of 2005. These promotions allowed the public to buy new cars at the same prices that employees paid, under a program of discounted prices formerly offered only to employees. While the promotions led to almost unprecedented sales increases, Busse et al. (2007) show that these demand increases cannot be attributed to price changes. All three manufacturers were offering deep discounts in the weeks before the promotion, and for many models the employee prices were *higher* than the prices immediately before the promotion. For these models, prices increased under the promotion, yet even on these models demand increased dramatically under the promotion. After ruling out alternative explanations, such as a change in advertising expenditure, the authors interpret the findings as evidence that the employee discount promotion acted as a price cue, persuading customers to purchase immediately rather than delay in anticipation of future discounts. Although there is evidence that customers engage in extensive price search when purchasing an automobile (see for example Bayus, 1991; Ratchford and Srinivasan, 1993; and Zettelmeyer et al., 2006), customers cannot search on 'future prices', and so they must rely on price cues to evaluate when to purchase. The findings are noteworthy because they demonstrate that customers also respond to price signals in a market in which high dollar values are at stake and customers engage in extensive information search.

Practitioners in the packaged goods industry also recognize that price cues can have a significant, positive impact on demand. For example, in a 1989 interview, a manager at H.E.B. Grocery Company commented:

> Occasionally we attach signs marked 'Everyday Low Price' in front of two randomly selected brands in several product categories throughout our store, leaving their prices unchanged. Even though customers should be accustomed to these signs and realize that the prices are unchanged, sales typically double for those brands that have the signs attached to their displays. I'm just amazed. (Inman et al., 1990, p. 74)

Explanations for why price cues are effective

Researchers have pursued different explanations for the effectiveness of price cues. Inman et al. (1990) extend the elaboration likelihood model (ELM) of Petty and Cacioppo (1986) to explain the consumer response to price cues. They argue that need for cognition plays a role in whether consumers respond to peripheral information, such as a price cue. Their laboratory experiments support this theory; they find that consumers who have low need for cognition are more likely to be influenced by a price cue.[2] The work of Inman et al. (1990) is grounded in psychology and provides a deeper understanding of consumer behavior. However, this research does not incorporate the perspective of the firm. In particular, given that price cues are effective and seemingly inexpensive to use, why not place them on many items?

Anderson and Simester (1998) provide an equilibrium explanation for the role of price cues that includes both the consumer and the firm. In their model, which we depict graphically in Figure 8.1, if customers lack sufficient price knowledge to evaluate whether a price offers good value, then demand does not respond to price changes alone. Instead,

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[2] Need for cognition (NFC) is measured using the 18-item NFC scale developed by Cacioppo et al. (1984).

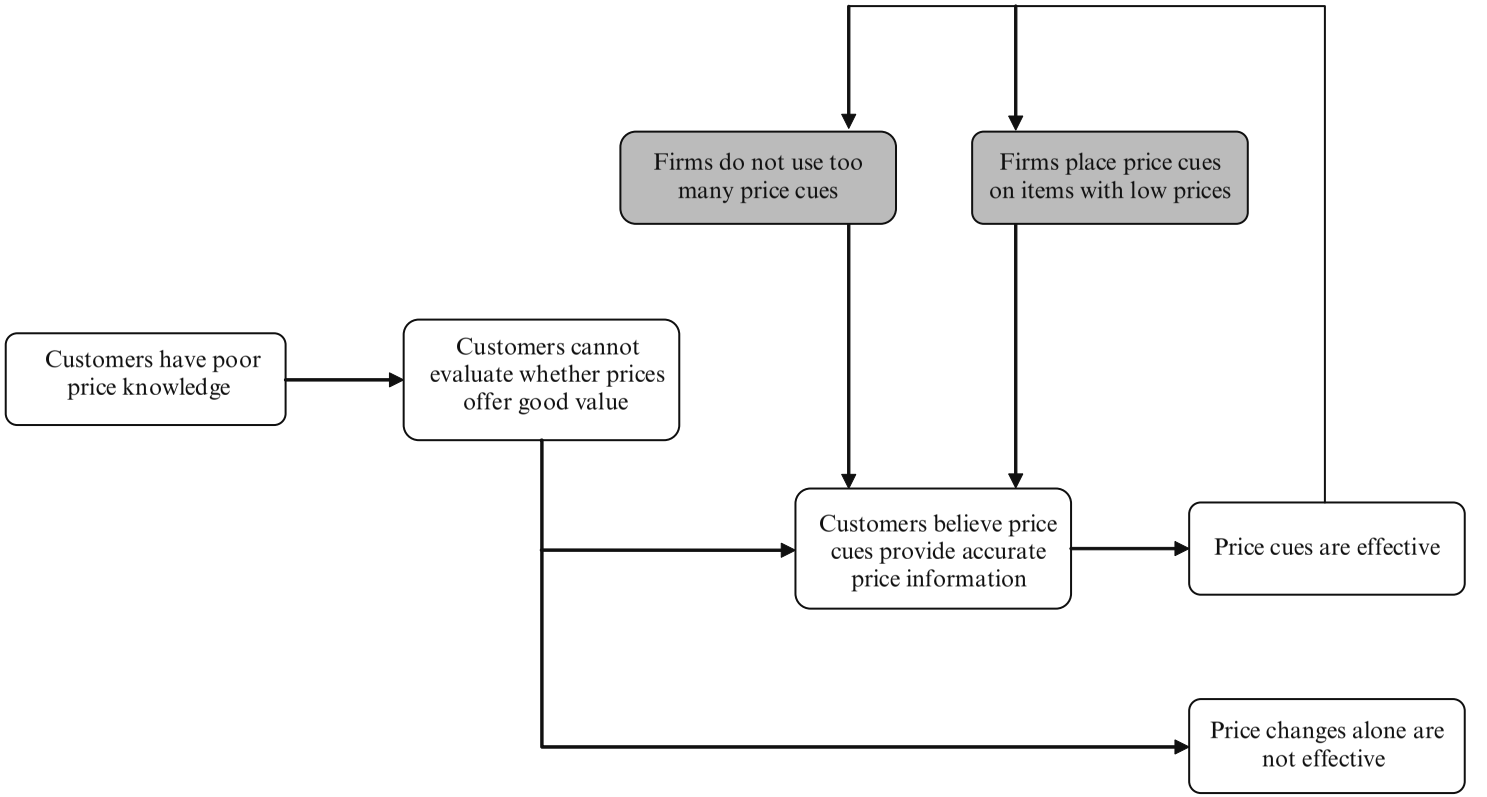

Figure 8.1 The equilibrium theory of price cues

customers turn to price cues to help judge value. Key to their model are the relationships connecting the firm decisions (depicted in the two shaded boxes) with customer decisions. These relationships ensure that retailers' price cue strategies and customers' purchasing behavior are both endogenous and rational. There are two key predictions. First, the model shows that if customers believe that products with price cues are more likely to be relatively low priced, firms prefer to place sale signs on lower-priced products. As a result, customers' beliefs are reinforced and price cues provide a credible source of information. Second, the authors show that if firms use price cues too frequently, customers will attribute less credibility to the cues and they lose their effectiveness. This in turn creates incentives for firms to limit the proliferation of the cues. These two predictions jointly imply that price cues are both self-fulfilling and self-regulating.

In 2001 the same authors (Anderson and Simester, 2001a) tested the second prediction by investigating whether price cues are less effective when used more often. The findings confirm that, holding price constant, overuse of sale signs can diminish their effectiveness. Support for this prediction is found in many industries, including women's apparel, toothpaste, canned tuna fish and frozen orange juice. For example, category demand for frozen orange juice decreases when more than 30 percent of items have sale signs. Similarly, category demand for canned tuna fish and toothpaste decreases when more than 25 percent of the items have sale signs. Notice that this effectively limits firms' use of price cues. Adding one more price cue to an item in a category increases demand for that item, but the other price cues in the category lose their effectiveness. When this second effect is large enough, there is eventually a decrease in category demand, which regulates overuse of the cues.

A recent large-scale field study with a chain of convenience stores has also directly evaluated the first prediction (Anderson et al., 2008). Although we delay a detailed discussion of this study until later in the chapter, the findings both confirm that it is profitable for firms to use price cues on items that are truly low priced, and diagnose why this is optimal.

Notice also that while the equilibrium framework reconciles the consistency of customer beliefs and firm actions, it does not speak to how these beliefs are created. It is sufficient that over time customers have learned to associate price cues with low prices, and that this understanding influences their purchasing behavior. Indeed, it is possible that customers' reactions to price cues occur at a subconscious level, so that they are not always aware that they are responding to the cues. The formation of customer beliefs and the extent to which customer reactions reflect conscious judgments both remain important unanswered research questions.

The role of reputations

Reputations provide another rationale for why firms may not use price cues in a deceptive manner (Tadelis, 1999; Wernerfelt, 1988). A firm's reputation may be irreparably damaged if consumers expect that a price cue signals a promoted price and later discover that the price is not discounted. Data from two competing retailers illustrate the pitfall of using sale signs deceptively. In spring 1997, we collected data from two retailers located approximately one mile apart in Rochester, New York. The retailers sold a broad range of electronics, home appliances and other hard goods. After several visits to both stores, we identified a set of 85 identical items sold by each retailer. We visited

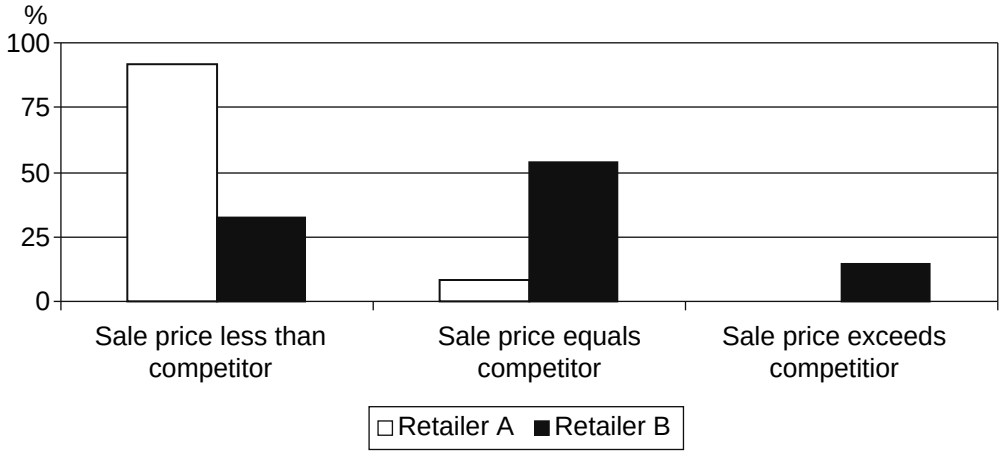

Figure 8.2 Accuracy of sale claims at two competing retailers

each store on the same day and collected the regular price and sale price (if discounted) for all 85 items.

In our analysis of the data we asked: 'Does the presence of a sale sign accurately convey that prices are low compared to a competing retailer?' To answer this question, we identified all cases where a product had a sale sign at one store but none at the competing store. If a sale item is truly low priced, we expect that the sale price should be less than the regular price of a competitor. More importantly, the sale price should never exceed a competing store's regular price. Our results are summarized in Figure 8.2.

The results showed that retailer A used sale signs to accurately signal that the current price was lower than competitors' prices. We found that 92 percent of the items marked as 'Sale' at retailer A were priced lower than at retailer B. For the remaining 8 percent of the observations the prices at the two retailers were identical. In contrast, at retailer B the presence of a sale sign was not nearly as accurate, and in many cases deceptive. We found that only 32 percent of the items marked with a sale sign at retailer B were lower priced that at retailer A. More striking was the fact that 14 percent of the items marked with a sale sign at retailer B had sale prices that exceeded the regular price at retailer A! Thus, while the sale items may have been discounted relative to past prices at retailer B, they were not low priced compared to the alternative of visiting retailer A.

In both cases, the retailers were using the sale signs in a manner that is somewhat 'noisy'. Retailer B was using the signs in a manner that was less informative and potentially misleading. Two years after this study, retailer B declared bankruptcy and went out of business. While we cannot claim a causal link between the retailer's financial distress and price cue policy, the anecdote does suggest that a firm's reputation can be damaged if price cues are used deceptively.

Price cues as information

The Anderson and Simester theory argues that price cues may serve an informational role when consumers have imperfect price knowledge. We consider a series of studies that support this view and illustrate other types of price cues.

Price endings

Academics have been fascinated by the use of 9-digit price endings for over 70 years (Ginzberg, 1936). This is in part due to their widespread use by US retailers – while estimates vary, as many as 65 percent of prices have been estimated to end in the digit 9. Despite this prevalence, there is relatively limited evidence documenting both their effectiveness and their role.

Some of the first evidence that 9-digit price endings can influence demand in retail markets is provided by Anderson and Simester (2003a), who present a series of three field studies in which price endings were experimentally manipulated in women's clothing catalogs. Their results confirm that in all three experiments a $9 price ending increased demand. This prompts the question: why are 9-digit endings effective?

Several competing explanations are reviewed by Stiving and Winer (1997), including the possibility that price endings serve as a price cue. For example, Schindler (1991) suggests that price endings provide information about relative price levels and/or product quality. In this theory, customers pay more attention to the right-most digits because of the information that they convey. This contrasts with the customer's emphasis on the left-most digits in the 'dropping off' theories. In those alternative theories, customers ignore the right-hand digits or place less emphasis on them.

There is both systematic and anecdotal evidence to support the view that price endings convey low prices. For example, Salmon and Ortmeyer (1993) describe a department store that uses a 0-cent ending for regularly priced items and 98-cent endings for clearance items. Similarly, Randall's Department Store uses 95-cent endings on all 'value' priced merchandise, which is 'meant to indicate exceptional value to the customer' (Salmon and Ortmeyer, 1992).

These anecdotes are supported by more systematic academic studies. Schindler and Warren (1988) show that one inference customers may draw from $9 endings is that a price is low, discounted, or on 'Sale'. More recently, Schindler (2006) analyzed prices for hundreds of different products that were advertised in several newspapers. Schindler shows that items priced with a 99-cent price ending are more likely to be in an advertisement that emphasizes price discounts.[3] He argues that this offers a plausible explanation for how consumers form associations between low prices and 9-digit price endings.

Anderson and Simester (2003a) provide further support for the theory that 9-digit prices convey information. They show that the increase in demand from a 9-digit item is greatest for new items that a retailer has not sold in previous years. Because customers have poor price knowledge for these items, this is precisely where price cues should be more effective. The authors also show that $9 price endings are less effective when retailers use 'Sale' cues. This is precisely what we would expect if the 'Sale' sign has already informed customers about whether an item is low priced.

Price promotions for new customers

New customers are typically least informed about prices, and so for these customers deep promotional discounts may act as a price cue and influence their overall price perceptions

[3] Schindler refers to these as low-price cues. We do not use this phrase, to avoid confusion with our definition of a price cue.

for a retailer. Bagwell (1987) presents an equilibrium model of initial prices as a cue that signals information about future prices.

There is also field research investigating this possibility (Anderson and Simester, 2004). The research includes three separate field experiments with a direct mail retailer that sells publishing products (books, software etc.). Study A was conducted using 56 000 existing customers. Studies B and C were conducted using 300 000 and 245 000 prospective customers identified from a rented mailing list. Each study used promotion and control versions of a test catalog sent to randomly assigned groups of customers. Prices in the promotion condition were 40 percent lower than in the control condition. The test catalog was otherwise identical and all of the customers received the same catalogs over the subsequent two years.

The results show that deep promotions have different long-run impacts on the behavior of new and established customers. The established customers in Study A reacted in the same manner as documented in other studies (see for example Neslin and Shoemaker, 1989). For these customers the short-run lift in demand was offset by a long-run decrease in demand, which almost certainly reflects the effects of intertemporal demand substitution (forward buying). In contrast, the deep promotions had a positive long-run impact on the demand of new customers (Studies B and C). Receiving deep discounts on their first purchase occasion prompted these customers to return and purchase 10 percent to 21 percent more frequently in the future. Further investigation suggests that the deep promotional discounts influenced the new customers' price perceptions. In this sense, the low initial prices served as a price cue about the overall level of prices.

Signpost items

Consider the purchase of a new tennis racket. The models change frequently and so most customers will be unsure how much a selected model should cost. On the other hand, most tennis players have good price knowledge of tennis balls. If they see a store charging $2 for a can of tennis balls, they may be reassured that they are not overpaying for the tennis racket. However, if the tennis balls are $5 per can, they may be better served purchasing their tennis racket elsewhere. Tennis balls are an example of a 'signpost' item for which many customers have good price knowledge. The price of a signpost item signals information about the prices of items for which price knowledge is poor. Other examples include customers using the prices of bread, milk or Coke to infer whether a supermarket offers good value on baking soda.

Simester (1995) presents an equilibrium model of the signaling role of signpost items. In his model, customers see the prices of a sample of 'advertised' items and use these prices to infer the price of the 'unadvertised' items for which prices are unobserved prior to visiting a store. The underlying signaling mechanism relies on correlation in the underlying costs (to the firm) of the different items. This can be compared with Bagwell's (1987) model of low initial prices, where the information revealed by a price cue depends upon correlation in the firm's costs over time. Simester tests his model using a sample of data from the Boston dry-cleaning market. He shows that the price to launder a man's shirt provides credible information about the cost to dry-clean suits and sweaters.

Price guarantees

A common strategy among retailers is to offer consumers a price guarantee. There are two widely used versions: price-matching policies and best price policies. A price-matching

policy guarantees that prices will be no higher than the prices charged by other retailers. A typical price-matching policy guarantees the consumer a rebate equal to the price (and perhaps more) if the consumer finds the same product offered at lower price by a competing firm within 30 days of purchase. Some firms, such as Tweeter, take the additional step of monitoring competitive prices for the consumer and sending the consumer a rebate automatically. While price-matching policies protect the consumer against price differences among competing retailers, best price policies protect consumers against future discounts within a retail store. For example, when a retailer discounts an item by 25 percent, a best price policy promises to refund this discount to all consumers who purchased the item in the previous 30 days.

Both types of price guarantees are intended to create the perception that an item is low priced compared to competing retailers (price-matching policy) or the firm's future prices (best price policy). Studies measuring the relationship between price guarantees and consumer price perceptions confirm that they can be an effective price cue, leading to more favorable price perceptions (see, e.g., Jain and Srivastava, 2000).

There is also evidence that price guarantees can affect price levels themselves, by influencing the intensity of competition. One stream of theoretical research suggested that these price guarantees may serve as a mechanism that raises market prices (Salop, 1986). Another stream suggested that these policies may increase competition in a market (Chen et al., 2001). These two streams of research show that whether price-matching policies lead to increased competition hinges on the degree of heterogeneity in consumer demand. This research has also highlighted subtle distinctions between price-matching, price-beating and best price policies. The empirical evidence is also mixed. Hess and Gerstner (1991) show that supermarkets that offer price-matching policies have less price dispersion and higher prices. In contrast, there is evidence that retailers who adopt price-matching policies reduce their prices. For example, when Montgomery Ward and Tops Appliance City introduced such policies they significantly lowered their prices (*PR Newswire*, 1989; Beatty, 1995; Halverson, 1995; Veilleux, 1996).

The moderating role of price knowledge

The Anderson and Simester model predicts that price cues will be most effective when consumers lack price knowledge. If consumers know that $4 is a relatively high price for a gallon of milk, then adding a price cue should have little impact on demand. But, if customers are uncertain about the relative price of milk, a price cue may affect purchase behavior. In a recent paper, Anderson et al. (2008) combine survey data and a field experiment to investigate this prediction. In their study, they survey customers and collect price recall measures for approximately 200 products. They then conduct a field experiment in which they randomly assign the same items to one of three conditions. In the control condition, items are offered at the regular retail price. In the price cue condition, a shelf tag with the words 'LOW prices' is used on an item. In the discount condition, the price is offered at a 12 percent discount from the regular price.

The authors show that both price cues and price discounts increase demand. But, consistent with theoretical predictions, they find that price cues are more effective on products for which customers have poor price knowledge. In contrast, price discounts are more effective when customers have better price knowledge. Thus discounting baking

soda from 99 cents to 89 cents is unlikely to be effective since customers have poor price knowledge for this product. But an offer of 'Sale 99 cents' may lead to a large increase in demand. Together these results highlight the importance that price knowledge has in determining the effectiveness of price changes and price cues.

Adverse effects of price cues

While price cues are intended to increase demand, retailers must recognize that they can also have an adverse impact on demand. Below we document three situations where a price cue reduced demand.

Regular price

When an item is offered at a discount, many customers are unable to recall the previous price. Including the regular price allows consumers to directly assess whether an item is low priced compared to past prices. One might be tempted to conclude that providing customers with this price cue would be beneficial, but a recent study we conducted with a direct mail company explains why this may not be correct. In this study, we varied the presence or absence of the regular price on a set of five dresses. For example, the regular price of one dress was $120 and it was discounted to $96. Customers who received the control catalog saw this dress offered at 'Sale $96'. Customers who received the test catalog saw 'Regular Price $120, Sale $96'.

The results of this study showed that demand significantly decreased when the regular price was included in the description. The presence of this price cue resolved customer uncertainty about the depth of discount. But the resolution of this uncertainty was unfavorable. In the absence of the regular price, customers expected to receive more than a $24 discount. Thus, while price cues can help resolve customer uncertainty, firms must also ask whether it is profitable to resolve the uncertainty. In some cases, customers may have more favorable price perceptions when they lack perfect information.

Installment billing

If customers lack perfect information about prices, they may also have imperfect knowledge of quality. Price cues are intended to create the perception of a low price and increase demand. But, if the price cue also creates the perception of low quality, then demand may decrease. For example, Fingerhut is a catalog retailer in the USA that offers installment billing on nearly all purchases. While Fingerhut also offers low-priced merchandise, it targets consumers with moderate to low incomes. This raises the possibility that consumers may believe that Fingerhut is positioned to offer both lower-priced and lower-quality items. If the quality inference dominates, then offering installment billing may adversely impact demand.

Anderson and Simester (2001b) document such an effect in a field experiment with a national mail order company. The research was conducted with a catalog that sells expensive gift and jewelry items and competes with retailers such as Tiffany's. In the experiment, customers were randomly mailed either a test or control catalog. The products and prices were identical except that the test catalog offered consumers the option of paying for their purchase with installment billing. For example, if a customer purchased a $500 necklace, the item could be paid for with a series of monthly payments rather than in a single lump sum payment. Installment billing was an optional feature and consumers who

received the test catalog were free to select either payment plan (i.e. installment billing or lump sum payment).

The authors show that the installment billing offer led to both a reduction in the number of orders received (13 percent) and a $15 000 reduction in aggregate revenue (5 percent). The sample sizes are very large and so the differences in the number of orders received between the test and control version are statistically significant ($p < 0.01$). The changes were economically significant and persuaded catalog managers not to include installment billing offers in future catalogs.

To further investigate these findings, the catalog agreed to survey their customers to measure how an offer of installment billing affects their customers' price and quality perceptions. Similar to the field test, two versions of a catalog were created and customers were randomly mailed a catalog along with a short survey. Respondents were asked to browse through the catalog and return their responses in a reply paid envelope. The findings confirm that offering installment billing lowers the perceived quality of the items in the catalog. Respondents in the test version were on average significantly more concerned about product quality than respondents in the control version. One respondent in the test version offered the following remarks: 'My reaction to this catalog is that people must be cutting back or not as rich as [the catalog] thought because suddenly everything is installment plan. It makes [the catalog] look tacky to have installment plans – kind of like Franklin Mint dolls.'

These findings contrast with earlier work suggesting that reframing a one-time expense into several smaller expenses can favorably impact demand (see, e.g. Gourville, 1998). The key distinction is the role of quality. In the installment billing study, product quality was not objectively verifiable, and so the installment billing cue not only influenced customers' price perceptions; it also lowered their quality perceptions. The same logic may explain why hospitals rarely use price cues to persuade customers that their prices are low.

Prices paid by other consumers

We have argued that price cues can convey information about competing prices, past prices or future prices. However, research on fairness suggests that whether consumers view a price as a good deal or a bad deal may also depend on what other consumers pay for similar products (Feinberg et al., 2002). Anderson and Simester (2007a) conduct a field experiment with direct mail apparel to investigate this issue. They conducted a split-sample test in which they experimentally varied the price premium on larger-sized women's dresses. In the control condition the prices of dresses did not vary by size. But, in three test conditions a premium of up to $10 was charged for larger-sized 4X and 5X dresses. For example, a size 3X dress may be priced at $39 and a 4X dress priced at $44. The experimental variation in prices enables the authors to examine how the price paid by other consumers affects demand.

The key finding is that customers who demand large sizes react unfavorably to paying a higher price than customers for small sizes. Further investigation suggests that these consumers perceived that the price premium was unfair. This finding is consistent with other evidence from the fairness literature, which contains many documented examples of customers reacting adversely when they perceive that prices are unfair (see, e.g., Xia et al., 2004; Anderson and Simester, 2007b).

Managing price cues

If price cues are effective, how should managers use them? The research reviewed in this chapter suggests that price cues are more effective among customers who lack price knowledge. Because we expect price knowledge to vary among products, a natural response is to use price cues on products for which customers have poor price knowledge. Similarly, price discounts are more effective when customers have better price knowledge. This creates an incentive to discount items for which customers have good price knowledge. Anderson et al. (2008) discuss why this presents a puzzle. For example, consider two items priced at $4 that differ in price knowledge. Suppose a firm lowers the price on an item with high price knowledge and uses a price cue on the other item. If firms pursue this strategy, then rational customers will infer that price cues are associated with products that are relatively high priced!

To address this issue, Anderson et al. (2008) identify three factors that moderate use of price discounts and price cues: total demand, margin and demand sensitivity. Holding all other factors constant, it is less profitable to use a price discount on a high-demand item due to the opportunity cost of a price reduction. Both price discounts and price cues are more profitable on high-margin items and on products with greater demand sensitivity. The question for managers is which of these three factors is most important?

To answer this question, the same authors conduct a large-scale field test with a convenience store chain in which they vary price discounts and price cues on almost 200 items. The authors analyzed which factors best explain the change in profits when a firm uses a price discount or a price cue. The results show that demand sensitivity is the overwhelming factor that drives incremental profits earned from both price cues and price discounts. Moreover, the sensitivity of demand is positively correlated across both treatments, so that items for which there is a greater price response are also items for which there is a greater response to price cues. This finding is important for both managerial practice and the academic theories we have discussed in this chapter. It implies that price cues and price discounts are likely to be used on the same items, and may help to resolve the apparent puzzle, explaining why price cues provide a credible signal of low prices.

A related concern of managers is how to use price cues in a competitive setting. Can price cues be an effective competitive tool? A recent study conducted with a German direct marketer of books examines precisely this question (Anderson et al., 2007). The company owns three different catalog companies that sell primarily books and music CDs. While the companies each have a distinct brand name, they are owned by a single firm. Importantly, from the consumer's perspective the three brands are viewed as competing retailers. This allows the parent company to study how price cues and price changes affect retail book competition.

The retailer conducted a field study in which it varied both prices and price cues on a set of 29 products sold by three different book retailers. The findings reveal that price cues lead to substitution between catalogs, confirming that they can be an effective competitive tool.

The study also showed that customer groups reacted quite differently to price cues and price changes. The company found that price cues were effective at increasing demand among moderate book buyers, but the demand increase did not come at the expense of competing catalogs. Instead, the increased demand from a price cue was incremental. In contrast, among heavy book buyers there was considerable evidence that price cues led

to store substitution. This understanding of consumer behavior offers deeper insight into the competitive nature of price cues. Surprisingly, the threat of a competing price cue is greatest among customers who are the heaviest buyers in a category.

Managing price knowledge

Because the effectiveness of price cues is moderated by customers' price knowledge, firms may also try to manage their customers' price knowledge. Indeed, the recent literature on price obfuscation suggests that customers' lack of price information may be partly attributable to the actions of the firms. The role that firms can play in hindering customers' ability to search for price information is investigated by Ellison and Ellison (2004). They argue that price obfuscation can mitigate price competition by reducing the perceived substitutability of the alternatives, and present evidence from the Internet suggesting that obfuscation may sharply increase margins on computer memory modules. They describe a variety of practices that firms use to obfuscate the price, including: introducing shipping costs and other price components; varying warranties, re-stocking fees and other contractual terms; varying prices and products across distribution channels; and/or using 'add-on' pricing in which the base product has inefficiently low quality.

Conclusions

The research on price knowledge reveals that there is an opportunity for firms to influence customers' price perceptions, while the research on price cues documents examples of firms exploiting this opportunity. There are several important conclusions. First, the range of cues available to firms is broad, ranging from explicit claims that prices are discounted to more subtle cues, such as 9-digit price endings, which may work even without customers recognizing their effect. Second, the cues are effective across many product categories. We have reported findings from studies conducted in a wide range of consumer markets, including consumables (toothpaste, canned tuna and frozen juice) and durables (apparel and publishing products). There is even evidence that the cues are effective in the market for new automobiles, where the prices are high and customers engage in extensive price search. Third, there is now a formidable collection of evidence that at least one reason price cues are effective is that they serve a signaling role, allowing customers who are poorly informed about prices to infer whether to search elsewhere for lower prices. This evidence includes investigations of several moderating effects, including: the role of customers' price knowledge, the effects on new versus mature products, and the effect on newly acquired versus established customers. Finally, there is evidence that price cues are not a magic panacea that firms can employ at will. The cues lose effectiveness the more often they are used, and so firms cannot simply place them on every product. Firms also risk lowering demand if they place them on items for which quality is uncertain (few patients are attracted to a cardiologist offering discounts) or if customers can see that other customers have the opportunity to purchase similar items at lower prices. On the other hand, firms that overlook the role of price cues, and focus solely on optimizing prices, forgo an opportunity to optimize profits.

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PART II

PRICING DECISIONS AND MARKETING MIX

9 Strategic pricing of new products and services*

Rabikar Chatterjee

Abstract

This chapter organizes and reviews the literature on new product pricing, with a primary focus on normative models that take a dynamic perspective. Such a perspective is essential in the new product context, given the underlying demand- and supply-side dynamics and the need to take a long-term, strategic, view in setting pricing policy. Along with these dynamics, the high levels of uncertainty (for firms and customers alike) make the strategic new product pricing decision particularly complex and challenging. Our review of normative models yields key implications that provide (i) theoretical insights into the drivers of dynamic pricing policy for new products and services, and (ii) directional guidance for new product pricing decisions in practice. However, as abstractions of reality, these normative models are limited as practical tools for new product pricing. On the other hand, the new product pricing tools available are primarily helpful for setting specific (myopic) prices rather than a dynamic long-term pricing policy. Our review and discussion suggest several areas that offer opportunities for future research.

1. Introduction

Pricing of new products is an especially challenging decision, given its critical strategic importance and complexity. Contributing to the complexity are the uncertainty faced by the firm on both demand and supply sides, the dynamic (changing) environment and operating conditions, and the need for a long-term decision-making perspective, given that the firm's pricing decision in the current period is likely to impact future outcomes. Thus this chapter focuses primarily on new product pricing strategies that take a long-term perspective and recognize the dynamics driven by demand- and supply-side conditions over the extended time horizon.

Past reviews of new product pricing models include Kalish (1988). Monroe and Della Bitta (1978), Rao (1984, 1993) and Gijsbrechts (1993) cover new product pricing as part of their broader reviews of pricing. Also relevant are the reviews of new product diffusion models incorporating price and/or other marketing mix elements by Kalish and Sen (1986) and Bass et al. (2000). This chapter provides a selective and updated review and synthesis of strategic new product pricing models, focusing primarily on analytical models, but also describing relevant empirical research.

1.1 Dynamic pricing of new products: skimming versus penetration

Dean's ([1950] 1976) seminal article identifies new product pricing policy as 'the choice between (1) a policy of high initial prices that skim the cream of demand [skimming] and (2) a policy of low prices from the outset serving as an active agent for market penetration [penetration pricing]' (p. 145). The rationale for these two extreme strategies lays the foundation for our subsequent review. As we shall see, some of the policy prescriptions call for

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a combination of penetration and skimming at different stages of the product life cycle, while others may be nuanced versions of these basic strategies. Dean identifies important elements of the new product pricing problem, including defining the firm's objective in terms of maximizing discounted profits over the planning horizon, taking into account customer and competitive dynamics over that period (see also Dean, 1969).

In a skimming strategy, prices begin high to extract the maximum surplus from customers willing to pay premium prices for the new product. Subsequently, prices decline as more price-sensitive segments are targeted in turn, to implement an intertemporal price discrimination strategy – 'an efficient device for breaking the market up into segments that differ in price elasticity of demand' (Dean [1950] 1976, p. 145). Dean also argues that this is a safer policy given uncertainty about demand elasticity, in that the market is more accepting of prices being lowered over time than the other way round. In addition, costs are likely to drop over time on account of market expansion and improved efficiency through experience (scale economies and experience curve effects). Price skimming helps to recover up-front investments in product development and introductory marketing. On the other hand, the high price level invites competition, unless the firm can extend its monopoly status (e.g. via patent protection).

Under a penetration pricing strategy, the objective is to aggressively penetrate the market by low prices. Some conditions under which penetration pricing makes sense are:

- price-sensitive customers in the mainstream market;
- short- and long-run cost benefits from scale economies and experience curve effects (cost-side learning), respectively;
- product characteristics that are well understood by mainstream customers (suggesting incremental rather than discontinuous innovations); and
- the threat of competitive entry.

Typically, a penetration pricing strategy would require the resources to support the rapid ramp-up in production, distribution and marketing of the product. Strategically, short-run profits are being sacrificed for future benefits – in terms of lower costs and a stronger market position, which can serve as sources of competitive advantage.

1.2 Skimming versus penetration: empirical evidence of managerial practice

When do managers use skimming or penetration pricing strategies in practice? Noble and Gruca (1999) surveyed managers responsible for pricing at firms supplying differentiated, capital goods in business-to-business markets, to learn about management practice and its relationship to theory. For new products, they identify three strategies – price skimming, penetration pricing and experience curve pricing (which is a particular case of penetration pricing).[1] The latter two involve low initial prices and have similar determinants relative to skimming – lower product differentiation, incremental innovation, low costs,

[1] Noble and Gruca's study is not limited to new products. They organize the strategies by the pricing situation for both new and mature products and then, for strategies within each pricing situation, by the conditions expected to favor the choice of a particular strategy. The three new product strategies were chosen by 32 percent of all respondents across all situations (skimming 14 percent, penetration 9 percent, and experience curve pricing 11 percent).

price elastic demand and available production capacity. The distinction is the primary source of cost advantage – experience curve pricing exploits learning by doing, while penetration pricing focuses on scale economies.

Managers were more likely to use skimming (with high relative price) in markets with high product differentiation when facing a cost disadvantage due to scale economies. Penetration pricing (with low relative price) was chosen when there was a cost advantage due to scale economies and total market demand was price elastic. Finally, experience curve pricing was used when there was high product differentiation, the product was not a major innovation, and there was low capacity utilization. Thus managerial practice is consistent with theory, except for the finding that experience curve pricing appears to be used in markets with high product differentiation, perhaps because the firms using this strategy are market followers cutting prices now to drive down costs in anticipation of future commoditization of the market.

Turning to a different industry (pharmaceuticals), Lu and Comanor (1998) investigate the temporal price patterns for new drugs and the principal factors affecting prices. Pharmaceutical price behavior appears consistent with Dean's conjecture. Significant innovations follow a modified skimming strategy, with prices at launch displaying substantial premium over existing substitutes, then declining over time. Most 'me too' new products follow a penetration strategy with launch prices below the competition, and then possibly increasing. Competition exerts downward pressure on prices. The nature of the application has pricing implications as well: drugs for acute conditions have larger premiums than those for chronic conditions.[2]

1.3 A framework for reviewing models of new product pricing

In the next two sections, we build on our discussion of skimming and penetration strategies to review analytical models of new product pricing that offer normative guidelines. With this in mind, we identify, in Table 9.1, the product, customer and firm/industry-related dimensions pertinent to the new product pricing decision that we employ to structure our review. Section 2 reviews models in a monopolistic setting, while Section 3 examines competitive models. Section 4 briefly discusses approaches to setting new product prices in practice. We conclude with a summary of the current status and directions for future research, in Section 5.

2. Normative models in a monopolistic setting

We organize our review of monopolistic models on the basis of the specification of the underlying demand model: models using an aggregate-level diffusion model for their demand specification (Section 2.1); models that consider the individual customer adoption decision explicitly in the diffusion process (Section 2.2); models incorporating strategic customers with foresight (Section 2.3); and models focusing on successive generations instead of a single product (Section 2.4). Section 2.5 summarizes the strategic new product pricing implications in a monopoly. Table 9.2 lists the key features and findings of selected monopolistic models.

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[2] For more on pricing of pharmaceuticals, see the chapter in this volume by Kina and Wosinska (Chapter 23).

Table 9.1 New product pricing models: key dimensions

Dimension	Characteristic	Remarks and implications
Product	Nature: frequency of purchase; physical product vs service	The frequency of purchase significantly impacts the dynamics of pricing. With durables, cumulative sales can adversely affect product demand owing to saturation; with nondurables, repeat purchase can build brand loyalty. Differences between physical products and services have pricing implications in general (see chapter).
	Degree of innovativeness	Products can range from radically new or breakthrough at one end of the spectrum to incremental (or 'me too') at the other. This dimension has a critical impact on the demand dynamics, via its influence on customer behavior and competitive advantage.
	Degree of customer involvement	With high-involvement products (e.g. large ticket items), customers are more inclined to make the purchase decision carefully, after collecting information to reduce the high degree of perceived risk, relative to low-involvement products (which are often purchased on impulse). For a new product, adoption behavior and, in the aggregate, the dynamics of demand are affected by the degree of involvement.
	Diffusion (positive network) effects	Positive network effects result in an increase in the value of products as the number of products in use in the market (e.g. fax machines) increases. This is a direct network effect. Similar positive effects can also be indirect – for example, customers' valuations of products (e.g. hardware) may increase from a greater availability of complementary products (e.g. software) as the installed base of customers expands (the 'complementary bandwagon effect', Rohlfs, 2001). The same dynamic of increasing likelihood of adoption with expanding usage base can result on account of 'word of mouth' effect (Rogers, 2003). We use the term *diffusion effect* to refer to the positive impact of market penetration (cumulative sales) on demand, whatever the underlying mechanism driving this dynamic.
Customer	Uncertainty, risk attitude and learning	In the new product context, customer uncertainty about product performance is a pertinent issue. When uncertainty is explicitly considered, customers' attitude toward risk and the possibility of learning to resolve uncertainty become relevant factors as well as influencers of customers' willingness to pay.
	Heterogeneity (in price sensitivity and other characteristics)	While price sensitivity obviously affects price, the heterogeneity in price sensitivity (and, more generally, in preferences) across customers provides opportunities for price-based segmentation, including intertemporal price discrimination. Individual-level price sensitivity may change over time, as in the case of increasing loyalty through product experience. The demand model may be specified at the aggregate level from the outset, or else built up from the

Table 9.1 (continued)

Dimension	Characteristic	Remarks and implications
		disaggregate level. The disaggregate approach allows for explicit consideration of heterogeneity on key behavioral dimensions (such as willingness to pay).
	Type of customer	The degree of customer sophistication (myopic versus far-sighted and strategic) affects the pricing decision. The type of buyer (organizational versus consumer) also affects the nature of buyer behavior, with implications for pricing practices and policy. In particular, organization buyers may be fewer in number but more powerful and sophisticated than individual consumers.
Firm and Industry	Cost structure (static and dynamic)	Apart from the 'static' aspects of the cost structure (fixed versus variable costs and economies of scale), experience curve effects – which result in a lowering of costs with the cumulative volume of units produced and sold – have a dynamic impact on new product pricing policy.
	Uncertainty and learning	There is uncertainty on the firms' part about demand for the new product as well as other aspects of the environment (e.g. the competition). Such uncertainty can impact on firm behavior. There may also be the incentive to learn (e.g. via experimentation).
	Competition	The competitive situation – the presence of competition and its nature – is a critical factor in the pricing decision. We classify new product pricing models on the basis of whether or not they consider competition. Among models considering competition, a distinction can be made between competition among incumbent firms and potential competition from future entrants (Chatterjee et al., 2000).

2.1 Aggregate-level diffusion models

There is a rich stream of literature in marketing on new product pricing models (typically normative in nature) based on aggregate-level diffusion models best exemplified by Bass (1969). A key idea underlying these diffusion models (applied to first-time sales of durables) is that the rate of sales at any point in time depends on the cumulative sales (or market penetration), i.e.

$$dN/dt = f(N(t)) \tag{9.1}$$

where $N(t)$ is cumulative sales (or penetration), dN/dt is the demand (rate of sales), and $f(\cdot)$ is the function operator. In particular, the Bass model takes the form

$$dN/dt = \left[p + q\frac{N(t)}{\overline{N}}\right][\overline{N} - N(t)] \tag{9.2}$$

where $\overline{N}$ is the size of the total adopter population, and p and q are the coefficients of innovation and imitation respectively. The underlying demand dynamics are driven by

Table 9.2 Normative models in a monopolistic setting

	(1) Robinson and Lakhani (1975)	(2) Dolan and Jeuland (1981)	(3) Kalish (1983)	(4) Bass and Bultez (1982)	(5) Krishnan et al. (1999)
1. Product characteristics	Durables	Durables and nondurables	Durables	Durables	Durables
2. Customer behavior/demand:					
(a) Demand drivers/sources of demand dynamics	Cumulative sales (diffusion and saturation effects), price	Durable: cumulative sales (diffusion and saturation effects), price. Nondurable (trial plus repeat): cumulative sales and price; saturation effects for trial	Cumulative sales (diffusion and saturation effects) or time (exogenous diffusion pattern), and price	Time (exogenous diffusion pattern), price	Cumulative sales (diffusion and saturation effects), price (current level and rate of change)
(b) Heterogeneity	No (aggregate-level specification)	No (aggregate-level specification)	No (aggregate-level specification)	No (aggregate-level specification)	No (aggregate-level specification)
(c) Uncertainty/ learning?	No	No	No	No	No
(d) Strategic customers?	No	No	No	No	No
3. Firm/industry:					
(a) Experience curve effects?	Yes	Yes	Yes	Yes	Yes
(b) Uncertainty/ learning?	No	No	No	No	No
(c) Decision variable(s)	Price	Price	Price	Price	Price
(d) Type of equilibrium (if customers are strategic)	Not applicable (myopic customers)	Not applicable (myopic customers)	Not applicable (myopic customers)	Not applicable (myopic customers)	Not applicable (myopic customers)

4. Key results/ pricing implications	• Optimal price may *increase* initially, and then *decline*	• Durables: optimal price *increases* initially, and then *declines* if diffusion effect sufficiently strong; otherwise price monotonically *declines* • Nondurables: optimal price monotonically *declines* if decline in trial (due to saturation) is greater than growth of repeat, and *increases* otherwise	• For durables (with diffusion and saturation effects), optimal price *increases* initially, and then *declines* if diffusion effect sufficiently strong; otherwise price monotonically *declines* • In case of exogenously specified life cycle, optimal price monotonically *declines* with experience curve effect on cost	• Optimal price monotonically *declines* with decreasing cost (experience curve effect)	• Optimal price may *increase* initially (if the diffusion price sensitivity parameter and discount rate are sufficient small), and then *declines*

	(6) Chen and Jain (1992)	(7) Raman and Chatterjee (1995)	(8) Huang et al. (2007)	(9) Jeuland (1981)	(10) Kalish (1985)
1. Product characteristics	Durables	Durables	Durables	Durables	Durables and nondurables
2. Customer behavior/demand:					
(a) Demand drivers/sources of demand dynamics	Cumulative sales (diffusion and saturation effects), price, uncertain discrete shock	Cumulative sales (diffusion and saturation effects), price, uncertainty (stochastic disturbance)	Cumulative sales (diffusion and saturation effects), price, reliability	Cumulative sales (information diffusion), distribution of reservation prices	Cumulative aware and cumulative adopters (awareness dynamics with saturation and diffusion effects), distribution of reservation prices

Table 9.2 (continued)

	(6) Chen and Jain (1992)	(7) Raman and Chatterjee (1995)	(8) Huang et al. (2007)	(9) Jeuland (1981)	(10) Kalish (1985)
(b) Heterogeneity	No (aggregate-level specification)	No (aggregate-level specification)	No (aggregate-level specification)	Heterogeneity in reservation price	No (aggregate-level specification)
(c) Uncertainty/ learning?	No	No	No	Yes – information reduces uncertainty	Yes – information reduces uncertainty
(d) Strategic customers?	No	No	No	No	No
3. Firm/industry:					
(a) Experience curve effects?	Yes	Yes	No	Yes	Yes
(b) Uncertainty/ learning?	Yes – random, discrete shock (Poisson process); no learning	Yes – demand uncertainty; no learning	No	No	No
(c) Decision variable(s)	Price	Price	Price, length of warranty, product reliability	Price	Price, advertising
(d) Type of equilibrium (if customers are strategic)	Not applicable (myopic customers)	Not applicable (myopic customers)	Not applicable (myopic customers)	Not applicable (myopic customers)	Not applicable (myopic customers)
4. Key results/ pricing implications	• Impact of uncertainty on price policy greater if probability and/ or magnitude of random shock is larger	• Demand uncertainty – *increases* initial price – *reduces* the price slope (which is declining)	• For particular set of parameter values, price and warranty period *decline* over time	• Same as aggregate-level models, i.e. optimal price *increases* initially, and then *declines* if diffusion effect sufficiently strong; otherwise price	• Industry prices will *increase* when diffusion effect is dominant and *decrease* when saturation effect is dominant

	• Impact of uncertainty can either reinforce or counterbalance price dynamics in deterministic case • Price path experiences jump at time of shock	– *reduces* sensitivity of initial price and slope to changes in other demand parameters and discount rate		monotonically *declines* • Actual shape of diffusion curve influenced by reservation price distribution	• Lower cost firm will have higher market share (with common industry prices) • Given cost-side learning, high-cost firm will produce more to reduce (or even reverse) cost disadvantage
	(11) Horsky (1990)	(12) Besanko and Winston (1990)	(13) Narasimhan (1989)	(14) Moorthy (1988)	(15) Balachander and Srinivasan (1998)
1. Product characteristics	Household durables	Durables	Durables	Durables	Durables
2. Customer behavior/demand:					
(a) Demand drivers/sources of demand dynamics	Cumulative eligible adopters (saturation and diffusion effects), preference, distribution of wage rates	Distribution of reservation prices, price, future price expectations	Cumulative sales, distribution of reservation prices, price, future price expectations	Distribution of reservation prices, price, future price expectations	Distribution of reservation prices, price, future price expectations
(b) Heterogeneity	Heterogeneity in wage rate	Heterogeneity in reservation price	Heterogeneity in reservation price	Heterogeneity in reservation price	Heterogeneity in reservation price
(c) Uncertainty/ learning?	Yes – information (cumulative sales) reduces uncertainty	No	No	Yes – uncertain about cost in Period 1	Yes – uncertain about extent of experience curve effect in Period 1
(d) Strategic customers?	No	Yes – perfect foresight	Yes – perfect foresight	Yes – perfect foresight	Yes – perfect foresight

Table 9.2 (continued)

	(11) Horsky (1990)	(12) Besanko and Winston (1990)	(13) Narasimhan (1989)	(14) Moorthy (1988)	(15) Balachander and Srinivasan (1998)
3. Firm/industry:					
(a) Experience curve effects?	Yes	No	No	No	Yes
(b) Uncertainty/ learning?	No	No	No	No	No
(c) Decision variable(s)	Price	Price	Price	Price	Price
(d) Type of equilibrium (if customers are strategic)	Not applicable	Subgame-perfect Nash	Subgame-perfect Nash	Subgame-perfect Nash	Subgame-perfect Nash
4. Key results/ pricing implications	• Optimal price *declines* monotonically if the diffusion effect is weak. If the diffusion effect is sufficiently strong, then prices start *low* and *increase* before *declining* • If the diffusion effect is especially strong, the initial price may be *lower* than initial cost	• Optimal price for firm facing myopic customers *declines* monotonically over time and is (a) *higher* (in case of myopic customers) and (b) *lower* (in case of strategic customers) in any time period (except last) than single-period optimal price • For any given penetration level, optimal price	• With customer expectations and diffusion, optimal price path follows cyclical pattern. Within each cycle, price declines monotonically • Stronger diffusion effect implies shorter cycles	• It is *not* possible for a low-cost monopolist to signal high cost by charging a high price in Period 1. The optimal decision is to price in Period 1 to reveal true cost	• Low-experience firm credibly signals its cost structure by charging a *higher* first-period price than in full-information case

		always *lower* for rational customers relative to myopic customers. Also, price declines at a *lower* rate			
	(16) Dhebar and Oren (1985)	(17) Judd and Riordan (1994)	(18) Zhao (2000)	(19) Bayus (1992)	(20) Padmanabhan and Bass (1993)
1. Product characteristics	Networked service (e.g. telecom)	Nondurable, experience good	Nondurable, experience good	Successive generations of durables	Successive generations of durables
2. Customer behavior/demand:					
(a) Demand drivers/sources of demand dynamics	Cumulative sales (positive network effect), distribution of reservation prices, subscription price	Distribution of customer's reservation price, product experience, price	Distribution of customer's reservation price, advertising (creates awareness), price	1st gen. (replacement sales only): cumulative 2nd gen. sales, prices, time; 2nd gen: cumulative 2nd gen. sales, prices	1st gen: cumulative firm sales (saturation effect), own price; 2nd gen: cumulative firm sales and own price, plus fraction of 1st gen. demand
(b) Heterogeneity	Heterogeneity in reservation price	Heterogeneity in reservation price	Heterogeneity in reservation price	No (aggregate-level specification)	No (aggregate-level specification)
(c) Uncertainty/ learning?	Yes – uncertain about future network growth (i.e. this can be only partially anticipated)	Yes – uncertain about product quality; learning from product use	Yes – uncertainty about product quality; inference drawn from firm's decisions (price, advertising)	No	No
(d) Strategic customers?	Yes – anticipate future network growth	Yes	Yes	No	No

Table 9.2 (continued)

	(16) Dhebar and Oren (1985)	(17) Judd and Riordan (1994)	(18) Zhao (2000)	(19) Bayus (1992)	(20) Padmanabhan and Bass (1993)
3. Firm/industry:					
(a) Experience curve effects?	Yes	No	No	No	Yes
(b) Uncertainty/ learning?	No	Uncertainty about quality – resolved by private information	No	No	No
(c) Decision variable(s)	Subscription price	Price	Price, advertising	Price	Price
(d) Type of equilibrium (if customers are strategic)	Subgame-perfect Nash	Bayes–Nash (subgame-perfect)	Separating equilibrium	Not applicable – myopic customers	Not applicable – myopic customers
4. Key results/ pricing implications	• Optimal subscription price monotonically *increases* over time • Anticipation of future network growth by customers and a lower discount rate both *lower* price for a given network size	• When customers are uncertain about product quality and form beliefs based on product experience and price, high-quality monopolist can signal quality by pricing *above* full-information price in Period 1. As consumer learning increases over time, price *declines* toward full-information level	• When customers are uncertain about product quality, a high-quality firm will price *higher* and spend less on advertising than in full-information situation, regardless of the quality–marginal cost relationship	• Optimal price for 2nd gen. *declines* monotonically over time if 2nd gen. sales come from normal and/ or discretionary replacements as long as fraction of normal replacements large enough. Otherwise, 2nd gen. price may be *increasing* initially	• Prior to 2nd gen. entry, diffusion (saturation) effect *decreases* (*increases*) 1st gen. price • After 2nd gen. entry, higher substitution rate drives 1st gen. price closer to, and 2nd gen. price away from, myopic optimum levels. Positive impact of 1st gen. price (sales) on 2nd gen. demand implies *higher* (*lower*) 1st gen. price

		• The firm has incentive for initial investment in temporary quality improvement	• For sufficiently large fraction of replacement sales, 1st gen. price *increases* (*decreases*) if 2nd gen. sales come entirely from discretionary (normal) replacements
	(21) Kornish (2001)		
1. Product characteristics	Successive generations of durables		
2. Customer behavior/demand:			
(a) Demand drivers/sources of demand dynamics	Prices and qualities of 1st and 2nd gen. distribution of reservation prices		
(b) Heterogeneity	Heterogeneity in reservation prices		
(c) Uncertainty/ learning?	No		
(d) Strategic customers?	Yes – perfect foresight		

Table 9.2 (continued)

	(21) Kornish (2001)
3. Firm/industry:	
(a) Experience curve effects?	No
(b) Uncertainty/ learning?	No
(c) Decision variable(s)	Price
(d) Type of equilibrium (if customers are strategic)	Subgame-perfect equilibrium
4. Key results/ pricing implications	• With customers with perfect foresight, it is possible for an equilibrium to exist in case there is improvement from 1st to 2nd gen. in real value terms, as long as firm does not offer special upgrade price for 2nd gen. to 1st gen. owners

the diffusion effect captured by the first term on the right-hand side of (9.2), which is increasing in cumulative sales or market penetration, and the saturation effect captured by the second term, which is decreasing in cumulative sales. The diffusion effect drives the dynamics early in the life cycle (when penetration is low), while the saturation effect dominates later – thus demand is increasing in cumulative sales (or market penetration) initially, but decreasing later in the life cycle. The models discussed in this section extend the basic model (9.1) by explicitly incorporating price as a variable influencing demand. Our discussion complements and updates the previous reviews by Kalish (1988); Kalish and Sen (1986); and Bass et al. (2000).

Normative models seek to derive the price trajectory over the planning period to optimize some objective (e.g. the discounted profit stream), given the demand function (based on a diffusion model), and appropriate initial, terminal and/or boundary conditions. Dynamic optimization typically involves the use of calculus of variations or optimal control (Kamien and Schwartz, 1991). Mathematically, the basic version of the problem may be stated as:

$$\max_{p(t)} \int_0^T e^{-rt}[p(t) - c(N(t))](dN/dt)dt \tag{9.3}$$

$$\text{subject to: } dN/dt = f(N(t), p(t)); N(0) = 0; N(T) = \varphi$$

where $c(N(t))$ is the marginal cost, which may decline in cumulative sales under cost-side learning, and φ represents the salvage value. The demand specification usually incorporates price in one of three ways (Kalish and Sen, 1986):

Multiplicative price influence The general form of the demand model is

$$dN/dt = f(N(t)) \cdot h(p(t)) \tag{9.4}$$

where $h(p(t))$ is a decreasing function of price at time t, $p(t)$. This model was first employed by Robinson and Lakhani (1975; Table 9.2(1)) and later by Dolan and Jeuland (1981; Table 9.2(2)); see also Jeuland and Dolan (1982). Dolan and Jeuland also analyze a non-durable goods model, where the sales rate is the sum of initial purchases given by (9.4) and repeat purchases proportional to the number of users $N(t)$.

Kalish (1983; Table 9.2(3)) considers a variety of demand specifications, including the multiplicative price influence model in (9.4). The Robinson and Lakhani (1975) and Dolan and Jeuland (1981) models are special cases of Kalish's more general formulation. The analysis provides insight into the effects of the different dynamic drivers of long-term profit on the optimal price path for a durable good. We summarize the key implications below:

- If demand is a function of price alone (i.e. there are no demand-side dynamics), the optimal price declines monotonically over time under cost-side learning and a positive discount rate. Cost-side learning reduces the optimal price below the myopic optimum, to trade off short-term profits for lower costs in future. This result applies to both durables and nondurables.

- In the presence of diffusion and saturation effects on demand, and assuming a zero discount rate, the optimal price path increases as long as demand is increasing in market penetration (i.e. the diffusion effect dominates), then decreases when demand begins to decrease with increasing penetration (i.e. the saturation effect dominates). The saturation effect in isolation indicates a higher price at any point in time than the corresponding myopic price, whereas the diffusion effect alone would indicate a lower price (to subsidize the early adopters and thereby stimulate the bandwagon effect for future profits).
- In the more realistic case of nonzero discount rate and cost-side learning, it is still optimal for prices to be increasing initially and then declining, as long as the diffusion effect is sufficiently strong and the discount rate is not too high. It pays to sacrifice early profits by subsidizing the early adopters, as long as the future is not discounted too heavily. Under a high discount rate and/or low diffusion effect, the optimal price path declines monotonically.
- In the case of nondurables (no saturation), the diffusion effect would imply a low initial price, increasing over time. Cost-side learning would also imply a lower price relative to the myopic optimum (at any point in time), but with a decreasing trajectory. Thus, with both diffusion and cost-side learning, the dynamic optimum price would be lower than the myopic optimum because both effects encourage stimulating sales now to drive up future demand and drive down future cost.
- In a trial/repeat model for nondurables, the optimal price declines (increases) monotonically if the decline in trial due to saturation is greater (lower) than the growth in repeat sales.

Multiplicative price influence on exogenous life cycle The general demand specification is

$$dN/dt = g(t) \cdot h(p(t)) \tag{9.5}$$

where $g(t)$ represents an exogenous life cycle, such as that generated by solving the Bass model (2) (Bass, 1980). Bass and Bultez (1982; Table 9.2(4)) and Kalish (1983) analyze this model, and find that the optimal price declines monotonically if there is cost-side learning. In this case, subsidizing early adopters does not help, since the exogenous life cycle specification does not incorporate the dynamic effect of price on demand as fully as the specification in (9.4).

Market potential as a function of price The demand model is of the general form:

$$dN/dt = f(N(t))[\overline{N}(p(t)) - N(t)] \tag{9.6}$$

where the market potential $\overline{N}$ is now modeled as a decreasing function of price and $f(N(t))$ represents the diffusion effect $[p + q[N(t)/\overline{N}]]$. Kalish (1983) examines this demand function as well, and shows that this case implies an initially increasing optimal price if the diffusion effect is sufficiently strong – qualitatively similar to the case of the multiplicative specification (9.4) discussed earlier. However, the condition for an increasing price trajectory is stronger, so that increasing prices will be less prevalent in this case

and, where they do occur, brief in their duration. Intuitively, increasing prices will have an adverse impact on the size of the potential adopter population, which is not an issue in the multiplicative price influence demand model.

The generalized Bass model (GBM) Bass et al. (1994) propose the generalized Bass model (GBM) in which $f(N(t))$ is given by the Bass (1969) model but $h(p(t))$ is replaced by a more general function that the authors term 'current marketing effort'. GBM models the effect of price differently from other multiplicative price influence models.

Krishnan et al. (1999; Table 9.2(5)) employ a slightly modified form of GBM to derive the optimal pricing strategy for new products, with the following current marketing effort function in place of $h(p(t))$ in (9.4):

$$x(t) = 1 + \gamma \ln p(0) + \beta \frac{\frac{dp(t)}{dt}}{p(t)} \tag{9.7}$$

where γ and β are both negative. Note that this specification models the impact of the absolute level as well as the slope of the price path on demand.[3] Under this formulation, the combination (actually, the product) of the diffusion price sensitivity parameter ($-\beta$) and the discount rate drives the optimal price path. If this combined effect is sufficiently small, the optimal price path is initially increasing and then declining; otherwise the path declines monotonically, as is often observed for many durables. In the multiplicative price influence models discussed earlier (Dolan and Jeuland, 1981; Kalish, 1983; Robinson and Lakhani, 1975), the price dynamics are driven by the demand dynamics (diffusion versus saturation), along with the discount rate and experience curve effects. In contrast, in the GBM formulation, the drivers are the diffusion price sensitivity and the discount rate (acting multiplicatively) and experience curve effects.

Incorporating demand uncertainty The models discussed above assume that demand is known with certainty over the entire planning horizon; realistically, firms launching new products are uncertain about demand over time. We review two models that explicitly incorporate different types of demand uncertainty. Chen and Jain (1992; Table 9.2(6)) consider uncertainty in the form of discrete shocks or 'jumps'. Raman and Chatterjee (1995; Table 2(7)) focus on demand uncertainty due to imperfect knowledge of the precise impact of explanatory variables included in the model as well as the 'random' impact of excluded variables.

Chen and Jain (1992) extend Kalish's (1983) deterministic model by including random shocks influencing demand. Their occurrence is governed by a Poisson process. Examples of such shocks are sudden changes to the potential market size or in economic conditions. The essential implications of Chen and Jain's analysis are:

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[3] While Krishnan et al. do not provide a behavioral justification for this specification, consideration of future expectations might suggest the inclusion of the price slope. However, the expectations argument would imply a positive sign for β.

- The impact of uncertainty on pricing policy increases the probability of the occurrence of the event and the magnitude of its after-effect.
- The impact of uncertainty can either reinforce or counterbalance the deterministic dynamic effects (as in Kalish, 1983), depending on whether the 'contingent experience effect' – the expected effect of cumulative sales on profits via its influence on the variation in the contingent state – is in the same or opposite direction as the deterministic experience effect.
- The price path experiences a jump at the time of occurrence of the contingent event.

Raman and Chatterjee (1995) incorporate the effect of demand uncertainty by allowing demand to be subject to stochastic disturbance. They find that, in general, the extent of impact of demand uncertainty on the optimal pricing policy is determined by the interaction among demand uncertainty, demand dynamics (diffusion and/or saturation effects), cost-side learning and the discount rate. For a Bass-type demand model with diffusion and saturation effects, they find (relative to the monotonically declining price path under deterministic demand in their infinite time horizon analysis) that:

- The effect of demand uncertainty is to (a) increase the initial price; (b) decrease the initial slope (that is, the price declines less steeply in cumulative sales); and (c) make the optimal price (both level and slope) less sensitive to changes in the discount rate or the coefficients of innovation and imitation that together determine the magnitude of demand dynamics.

Intuitively, uncertainty moderates the impact of the variables driving optimal price dynamics.

Incorporating the manufacturing–marketing interface In an interesting cross-functional modeling endeavor, Huang et al. (2007; Table 9.2(8)) develop a model that includes product reliability, Bass-type demand-side dynamics and cost-learning effects. The decision variables are product reliability (at the design stage) and dynamic policies over the planning horizon with regard to (i) price and (ii) length of the warranty. Given the complexity of the model, general qualitative implications are difficult to articulate, although the authors identify the direction of the slopes of the price and warranty policy paths for different conditions relating to the current value Hamiltonian and demand dynamics (diffusion versus saturation). Further, they provide numerical examples to demonstrate how dynamic programming may be employed to derive optimal policy. For a particular set of parameter values, it is shown that both optimal price and warranty period decline over time. This model represents a valuable (and rare) effort to capture the cross-functional aspects of decisions involving new products.

2.2 Models considering the individual customer adoption decision

The models discussed in Section 2.1 specify demand at the aggregate level, without really explicitly considering the customer adoption process. We next examine three models proposed by Jeuland (1981), Kalish (1985) and Horsky (1990) (Table 9.2(9), (10) and (11)) that extend the aggregate diffusion model paradigm to include aspects of the adoption process leading to an explicit adoption decision rule at the disaggregate level.

This provides potentially richer implications for new product pricing that augment the findings from the aggregate models. These models postulate that (a) the population is heterogeneous in their reservation price for the new product, (b) potential adopters are uncertain about its performance, lowering their reservation price, (c) information from adopters and other sources reduces this uncertainty, and (d) an individual adopts the product once its price falls below her reservation price.

Jeuland (1981) assumes that uncertain potential adopters believe that there is some probability that product performance will be lower than its true level. Once they are informed of the true performance (through word-of-mouth from adopters), their reservation price jumps up. The dynamics are thus driven by (a) the information diffusion process (which follows a process governed by the model (2) with the coefficient $p = 0$), and (b) the pricing policy. Qualitatively, the optimal pricing policy implications are similar to those for the aggregate-level multiplicative price influence models discussed earlier. However, the distribution of reservation prices across the population affects the specific trajectory of the optimal price path over time.

Kalish (1985) includes an explicit awareness component in his framework. At any point in time, individuals in the population belong to one of three stages: (a) unaware; (b) aware but yet to adopt; and (c) adopter. Awareness of the new product diffuses according to a model similar to (2), with the coefficient of innovation p a function of advertising, and word-of-mouth generated by both groups (b) and (c), with different coefficients of imitation q_1 and q_2, respectively. Aware customers are still uncertain of their valuation; this uncertainty decreases as the number of adopters increases. Aware customers become potential adopters when their risk-adjusted valuations exceed the price. These potential adopters actually adopt the product gradually after this adoption condition is met, with a constant conditional likelihood of adoption (hazard rate). The implications of Kalish's model for durable and nondurable goods are as follows:

- *Durable goods* The optimal price decreases monotonically, unless adopters are highly effective in generating awareness and/or early adopters reduce their uncertainty significantly. In the latter case, prices may increase at product introduction, when customers are the least well informed and the marginal value of information is the highest.
- *Nondurable goods* For constant marginal cost (i.e. no cost-side learning), the optimal price will increase to some steady-state level, if and only if advertising is decreasing, which is the case unless the discount rate is high.

These results for durable and nondurable goods are qualitatively consistent with the implications of the aggregate-level models, with the added insight into the role of uncertainty reduction.

Horsky (1990) uses a household production framework to show that individual (or household) reservation prices depend on product benefits and wage rates. Assuming an extreme value distribution for the wage rate across the population yields a logistic adoption function, dependent on the wage rate distribution parameters and the price. These 'eligible adopters' may delay their purchase because of unawareness, product performance uncertainty, or expectations of a price decline, all of which are assumed to decrease in cumulative sales. The resulting diffusion model reduces to the 'market potential as a

function of price' form in (9.6), with the eligible adopters (obtained from the logistical adopter model) as the potential adopters.

Given the model set-up, the results are consistent with those of the aggregate-level 'market potential as a function of price' model (Kalish, 1983). If the diffusion effect is weak, the optimal price path declines monotonically. If it is sufficiently strong, then prices start lower to subsidize the early adopters and rise before declining. If the effect is especially strong, the initial price may actually be lower than the initial marginal cost, implying negative early contribution.

In summary, the pricing implications of these three models are broadly consistent with the aggregate-level diffusion models discussed in Section 2.1. However, they add nuances to the implications by virtue of their disaggregate-level behavioral assumptions – in particular, the distribution of reservation prices (wage rates in Horsky's model) in the population influences the price trajectory. While these models consider the individual-level adoption decision and thereby incorporate heterogeneity, the dynamics of demand are largely driven by the model components (e.g. awareness) based on an aggregate diffusion model specification, e.g. Bass (1969).

2.3 Models incorporating strategic customers with future expectations

With time-varying price paths, customers may form expectations of future prices (or product performance) and take these future expectations into account while making their current purchase decisions. The models discussed so far effectively ignore the role of customer expectations, assuming that customers act myopically.[4] We now examine models explicitly incorporating customer expectations. These models are commonly based on rational expectations – implying that, in equilibrium, customers correctly predict the pricing policy to be followed by the monopolist. While as a descriptive model of customer behavior the rational expectations assumption is perhaps unrealistic in terms of the implied customer sophistication, its use as a paramorphic ('as if') modeling device in predicting outcomes in dynamic economic systems (including a firm's pricing policy) is widely accepted.

Besanko and Winston (1990; Table 9.2(12)) show how customer foresight influences a durable goods monopolist's price-skimming strategy over multiple time periods. Customers are intertemporal utility maximizers with rational expectations and constant reservation prices that are uniformly distributed over the population. The subgame-perfect Nash equilibrium analysis compares the dynamic pricing implications in the case of rational customers (with perfect foresight) with that of myopic customers.[5] The key findings are as follows:

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[4] Kalish (1985) and Horsky (1990) mention future expectations, but do not incorporate them formally in the model.

[5] A subgame-perfect Nash equilibrium is a Nash equilibrium whose strategies represent a Nash equilibrium for each subgame within the larger game. Limiting the equilibrium to be subgame-perfect rules out unreasonable commitments by the firm (such as committing to not lowering prices in the future, when such lowering will always be profitable).

- The optimal pricing policy for a firm facing myopic customers declines monotonically. The price is higher than the single-period profit-maximizing price in each period except the last.
- The policy for a firm facing rational customers also declines monotonically. However, the price is lower than the single-period profit-maximizing price in each period except the last.
- For a given penetration level, optimal prices are always lower and their decline more gradual, for rational customers. The first-period price for myopic customers is higher, although at some point in time this price may drop below that for rational customers.
- Using a pricing policy that is optimal for myopic customers when the customers are actually rational leads to suboptimally high prices initially and lower profits overall.

Comparing the multi-period versus the single-period case, a higher price in any period but the last makes sense for myopic customers because the firm can sell to those who have not yet bought in a future period, at lower prices. However, with rational customers, this effect is more than offset by the greater price sensitivity of customers who are willing to wait for prices to drop if there are future periods. Thus, with myopic customers, a firm would prefer as many periods (or opportunities to drop its price) as possible within the overall time horizon, for more effective skimming. With rational customers, it is the opposite – a shorter time horizon, or fewer but longer periods within the horizon, is preferred. The challenge for the firm is to be able to credibly commit to holding prices constant over the longer time period.

Besanko and Winston's analysis provides important insights into the impact of customer foresight, in isolation from other dynamics such as positive network effects (which would imply that reservation prices increase with market penetration, rather than being constant).

Narasimhan (1989; Table 9.2(13)) incorporates rational customers along with diffusion effects, assuming two types of customers differing in their reservation prices. New customers enter the market in each period, with the number given by a Bass (1969) type diffusion model. Once they enter the market, customers exit only after making their purchase of the durable. The purchase decision is based on maximizing intertemporal surplus. The key results are as follows:

- The optimal price path follows a cyclical pattern. Over each such cycle, the price declines monotonically from a high level (to sell to the high-valuation customers) and ends at a low level (for one period) to sell to the accumulated stock of low-valuation customers before returning to the high level. Customer expectations limit the price decline within each cycle.
- The length of the price cycles and the depth of discount depend on the relative sizes and valuations of the two segments, and the diffusion model coefficients. A higher coefficient of imitation implies shorter cycles to profit from early market penetration.

While these cyclical pricing implications are interesting, it is not clear if the same effect will persist if the distribution of reservation prices is continuous (e.g. uniform) across the

potential adopters, rather than dichotomous, as assumed. Also, as Narasimhan points out, prices would decline monotonically without cycling if the high-valuation customers entered first, which seems more plausible than both customer types entering in a fixed ratio in each period.

Moorthy (1988; Table 9.2(14)) considers a two-period model with uniformly distributed reservation prices across customers. Customers are uncertain about the cost of the durable, and use the first-period price to form expectations of the second-period price. The question is: can a low-cost monopolist pretend to have a high cost and thereby charge a high price in the first period, before dropping prices in the second period to exploit its low costs? The analysis shows that this is not possible – the firm's optimal decision is to price such that it reveals its true cost in the first period. This result suggests some robustness to the implications of the rational expectations model: the firm cannot 'fool' the customers even if they do not know the product cost.

In a similar vein, Balachander and Srinivasan (1998; Table 9.2(15)) analyze a two-period model in which rational customers with uniformly distributed reservation prices are uncertain about the degree of the firm's cost-side learning (high or low). The first-period price serves as a signal for customers to update their beliefs. The analysis yields a separating equilibrium in which a slow learning firm credibly signals its cost structure by charging a higher first-period price than if customers were fully informed. The signal is credible because a fast learning firm would charge a lower price to benefit from the experience curve effect in the first period.

In contrast to the above models focusing on durables, Dhebar and Oren (1985; Table 2(16)) consider a networked service (such as telecom) where customers can choose to subscribe period by period, with no start-up or termination fee (so that price expectations are not a factor). The value of the service depends on the price (subscription rate) and the number of subscribers. The optimal price path increases monotonically over time, consistent with the results for nondurables in Sections 2.1 and 2.2. Further, by anticipating future network growth, customers lower the equilibrium price (for a given network size) and thereby enlarge the network. A lower discount rate also has the effect of lowering price and enlarging the network.

Dhebar and Oren (1986) extend their 1985 model to consider nonlinear pricing where customers decide on usage volume in addition to subscription. They show that a nonlinear price schedule, consisting of a subscription price and a volume-based usage charge, results in a larger equilibrium network and higher profits than under a policy in which all subscribers pay the same fixed fee irrespective of usage. Dhebar and Oren's research focuses on networked services, which includes an increasing range of applications in today's technology-driven environment.

Price as signal of quality Can price serve as a credible signal of quality when there is uncertainty about quality? Research in economics (e.g. Milgrom and Roberts, 1986; Bagwell and Riordan, 1991) has shown that a high-quality firm may signal its quality via a price higher than the full-information optimum, if the high-quality firm's cost is sufficiently higher than that of the low-cost firm. Judd and Riordan (1994; Table 9.2(17)) use a signal-extraction model of customer behavior to explore this issue in the absence of any cost difference between the low- and high-quality firms. Customers' beliefs about the value of the product depend on their individual experience with the product as well

as the inference drawn from the price. The former makes it harder for the firm to deceive the customer. The two-period analysis shows that:

- When customers, uncertain about product quality, form beliefs based on both their product experience and the price, the high-quality monopolist can signal quality by initially pricing above the full-information price even if the high- and low-quality products have the same cost. As consumer learning increases over time, prices decline toward the full-information level.
- Firms have an incentive to invest in temporary enhancement of quality initially, to influence customers' beliefs about quality for future benefit.

Zhao (2000; Table 9.2(18)) includes advertising as a decision variable in addition to price in a quality signaling modeling framework. Advertising serves not just as a signaling device (as in Milgrom and Roberts, 1986), but also as a generator of awareness. The analysis shows that a high-quality firm will price higher and spend less on advertising when customers are uncertain about quality than in the full-information situation. Thus, high price signals high quality in this case, as it does in the price-only models. In contrast to the situation where advertising's only role is to signal quality, it is optimal to spend less on advertising when it also creates awareness.

2.4 Models incorporating successive generations of new products

We next review models focusing on successive generations of a product, where the next generation is an advanced version of the current one, and gradually replaces the latter.

Aggregate-level diffusion models Bayus (1992; Table 9.2(19)) models the sales of a next-generation durable considering the replacement behavior of the previous generation. The time horizon begins with the introduction of the second generation (G2). At the start, there is a fixed population of owners of the first generation (G1). At any point, some proportion of the installed base of G1 will require to be replaced. These 'normal' replacements may be sourced from either G1 or G2. In addition, the rest of the installed base is susceptible to making 'discretionary' (accelerated) replacements on account of the availability of G2 – these sales are influenced by the diffusion effect. Mathematically, sales of G2 are given by:

$$dN(t)/dt = [\overline{N} - N(t)]\,\{\,[1 - \theta\,(p_1(t), t)]f\,(N(t)\,)\,g\,(p_2(t)\,) + \theta\,(p_1(t), t)\,\varphi(p_1\,(t), p_2(t)\,)\,\} \tag{9.8}$$

where $N(t)$ is cumulative second-generation sales, $\overline{N}$ is the initial market size (G1 installed base at the time of G2 introduction), $p_1(t)$ and $p_2(t)$ are G1 and G2 prices, respectively, $\theta(p_1(t), t)$ is the fraction of G1 installed base making 'normal' replacements at time t, $\varphi(p_1(t), p_2(t))$ is the fraction of 'normal' replacements sourced by G2, and $f(N(t))$ is the diffusion effect. Thus G1 sales equal $[\overline{N} - N(t)]\theta(p_1(t), t)\,[1 - \varphi(p_1(t), p_2(t))]$. The optimal G1 and G2 price paths can assume various patterns depending on specific conditions, indicating the complexity that consideration of successive generations with

overlapping sales adds to the pricing decision. However, for a sufficiently long planning horizon, the following results hold:

- The optimal price for G2 declines monotonically if G2 sales come from only 'normal' or both 'normal' and 'discretionary' replacements; or from only 'discretionary' replacements as long as the fraction of 'normal' replacements θ is sufficiently large. If θ is not large enough, the optimal price may be increasing initially. Thus the G2 price path declines when replacement is important (even without cost-side learning) because the initial G2 sales are sourced by G1 replacements and therefore no subsidization of early adopters is necessary.
- For a sufficiently large fraction of 'normal' replacement sales, the optimal price for G1 monotonically increases [decreases] if G2 sales come entirely from 'discretionary' ('normal') replacements. Thus the G1 price trajectory is heavily influenced by replacement behavior and the source of second-generation sales.

Bayus provides some empirical support for his results, using successive generations of different consumer durables (B&W/color TV; CD/LP record players; corded/cordless/cellular telephones).

Padmanabhan and Bass (1993; Table 9.2(20)) analyze a successive-generations model, with only the first generation (G1) available in the first part of the planning horizon, until the second (advanced) generation (G2) is introduced at some exogenously determined point. The demand specification is fairly general, in order to capture a variety of possible demand dynamics:

$$\text{G1: } dN_1(t)/dt = (1-\theta)f(N_1)(t), p_1(t) \quad \text{and} \tag{9.9}$$

$$\text{G2: } dN_2(t)/dt = g(N_1(t), N_2(t), p_1(t), p_2(t)) \tag{9.10}$$

where $N_1(t)$, $N_2(t)$ are the cumulative sales of G1 and G2, $p_1(t), p_2(t)$ are the G1 and G2 prices, and θ is the fraction of first-generation sales switching to the second generation ($\theta = 0$ prior to G2 introduction, and some constant value $0 < \theta < 1$ thereafter). Thus, after the introduction of G2, some (fixed) fraction of G1 sales is cannibalized by G2, which also generates sales from its independent market potential. The model may be viewed as a successive-generations extension to Kalish (1983), with the following implications:

- Prior to G2 entry, a positive impact of additional G1 sales on G2 demand (diffusion effect) reduces the G1 price. If the impact on G2 demand is negative (saturation effect), then the G1 price increases. Otherwise, the G1 price slope is in line with Kalish (1983).
- After G2 entry, a higher substitution rate θ drives the G1 price closer to, and the G2 price away from, their myopic optimal levels. Also, if G2 sales are increasing in the G1 price, the latter is higher to sell more of G2. However, a positive impact of G1 sales on G2 demand implies a lower G1 price to stimulate G1 sales. The net effect depends on the relative strengths of these factors. The G2 price trajectory is otherwise in line with Kalish (1983).

One interesting implication of both models is that it may sometimes be optimal to actually increase the price of the first-generation product after the introduction of the next generation: all else equal, a higher G1 price is likely to have a positive impact on G2 demand.

Successive generations and strategic customers with perfect foresight Since customers with perfect foresight can anticipate the introduction of a superior product, what are the implications for strategy? Using a two-period model, Dhebar (1994) shows that if the technology improves too rapidly (so that the product improves in 'present value' terms), there is no equilibrium because the monopolist has the incentive to target customers who did not buy in the first period with low second-period prices. High-end customers are tempted to wait for the improved product. Thus there is a demand-side constraint imposed on the rate of product improvement.

Kornish (2001; Table 9.2(21)) uses a two-period model similar to Dhebar's, but assumes that if both generations were free, customers would be better off having G1 in period 1 and then switching to G2 in period 2 rather than waiting for G2. Under these assumptions, an equilibrium can exist if the successive generations imply improvement in 'real value' terms, as long as the monopolist does not offer a special upgrade price for G2 to current G1 owners. For the monopolist to credibly commit to such a single price in Period 2, he would need to make it impossible for a G1 owner to distinguish herself from a non-owner (e.g. by setting conditions that were either too difficult to prove, or too easy to claim, G1 ownership).

2.5 Normative models in a monopolistic setting: summary of implications

To conclude this section's review of monopolistic models, we summarize the main (and robust) implications for new product pricing strategy from the literature. The dynamic optimum policy is contrasted with the short-term (myopic) optimum that ignores the future profit implications of current decisions. We focus on the effect of individual factors – typically, when several factors operate simultaneously, the net impact depends on their relative strength.

- *Cost-side learning* Experience curve effects lower the optimal price (at any point in time) relative to the myopic optimum, while the dynamic optimal price declines over time.
- *Demand-side learning (diffusion effect)* The diffusion effect lowers the optimal price relative to the myopic optimum; the dynamic optimal price increases over time.
- *Demand saturation (for durables)* Saturation increases the optimal price relative to the myopic optimum; the dynamic optimal price decreases over time.
- *Demand dynamics for durables* For durables, saturation becomes the dominant effect over time relative to diffusion, as the market saturates. If the diffusion effect is sufficiently strong, the optimal price starts low to subsidize early adopters, then increases before declining.
- *Nondurables: net impact of demand- and cost-side learning* The optimal price is lower at any point in time than the myopic optimum, while its slope depends on the strength of demand-side learning (from diffusion and/or learning-by-use) relative to cost-side learning.

- *Random demand shock* The likelihood of a random shock impacts the price path. The degree of impact depends on the probability of occurrence on the event and the magnitude of its after-effect. The price path itself will exhibit a jump at the time of the shock.
- *Demand uncertainty* The impact of demand uncertainty is to make the optimal price less sensitive to the demand dynamics relative to the deterministic case.
- *Customer heterogeneity in willingness to pay in a durable goods market: myopic customers* In the absence of other effects, the optimal price follows the classic skimming strategy, with prices starting high to target the high-valuation segment and then declining over time to target successively lower-valuation segments. In each period, the price is higher than the single-period optimum.
- *Customer heterogeneity in willingness to pay in a durable goods market: strategic customers with perfect foresight* In any period, the optimal price is lower than the single-period optimum if customers have perfect foresight. Relative to the strategy for myopic customers, the starting price is lower and the price decline is more gradual when customers are strategic.
- *Services with positive network effects* The optimal price of a networked service (such as telecom) is monotonically increasing over time. Anticipation of future network growth (by strategic customers) serves to lower the price for a given network size.
- *Signaling cost structure (durable goods)* If customers are uncertain about the firm's cost structure, the firm should set the first period price to reveal its true cost structure, rather than masquerading otherwise. Similarly, if the uncertainty is about the rate of experience-based cost reduction, it may be optimal for a firm with a low learning rate to signal this via an initial price that is higher than the full-information optimum.
- *Signaling by the firm under customer uncertainty about quality (nondurables)* A high-quality firm can signal quality by pricing higher than the full-information optimum. Prices decline over time (toward the full information price) with customer learning.
- *Successive generations (durable goods)*
  - The price of the second generation is more likely to be monotonically declining from the outset than for a single new product, because sales from replacement of the first generation reduce the need to subsidize early adopters.
  - The price of the first generation after introduction of the second generation depends heavily on replacement behavior and the source of second-generation sales.
  - The first-generation price prior to introduction of the second generation decreases (increases) if the impact of additional first-generation sales on the potential market for the second-generation is positive (negative).

3. Normative models in a competitive setting

The models reviewed in Section 2 assume the absence of competition, which may be reasonable for major innovations early in the life cycle, or else if the focus is at the industry level ignoring interfirm competition. The presence of competition, involving incumbent firms or potential entrants, can significantly influence new product pricing strategy.

Section 3.1 briefly introduces the methodology used to analyze competitive models. Section 3.2 reviews models that consider potential competition, with a firm enjoying monopoly status prior to competitive entry, while Section 3.3 reviews models incorporating competition among incumbent firms. Section 3.4 summarizes the strategic new product pricing implications in a competitive setting. Table 9.3 presents the key features and findings of selected competitive models.

3.1 Equilibrium strategies in competitive situations

In a competitive situation, a firm's performance and its best (profit-maximizing) decision is usually affected by the actions of the other competing firms. Analytical models typically employ a game-theoretic framework to obtain a non-cooperative Nash equilibrium solution, such that no firm has an incentive to unilaterally deviate from the equilibrium.[6] As discussed earlier, the new product pricing decision should be in the form of a policy over time, considering the dynamic setting. The competitive counterpart to the optimal control formulation discussed in Section 2.1 is the differential game, which is employed to seek an equilibrium trajectory of the decision variable(s), where the objective of the firms is typically to maximize discounted profits over the planning horizon (Dolan et al., 1986; Dockner et al., 2000).

Two types of Nash equilibria are pertinent in the case of differential games. Open-loop equilibria express the policies as functions of time alone, while closed-loop equilibria are functions of time and the state of the system (e.g. cumulative sales). The strategies under the two equilibria are generally different, as illustrated later. Open-loop strategies are determined and committed to by the competitors at the outset for the entire planning horizon. Closed-loop policies capture the dynamics of competitive interaction by allowing strategies to adapt to the evolving state of the system over time. Closed-loop policies recognize that the best decision for a firm at any point in time is influenced by the positions (states) of its competitors, and are thus more appealing conceptually, though usually more difficult to derive analytically.

3.2 Models considering potential competition

Durable goods models with saturation effects We review two models that address the issue of potential competitive entry in a currently monopolistic market. Eliashberg and Jeuland (1986; Table 9.3(1)) analyze pricing strategies from the perspective of the first entrant, in a durable goods market. This firm enjoys monopoly status, until the second firm enters (at an exogenously specified point). Sales dynamics are driven by saturation effects alone and the price, with the following specification for the monopoly and duopoly periods:

$$\text{Monopoly: } dN_1(t)/dt = [\overline{N} - N_1(t)]\alpha_1[1 - kp_1(t)], \quad 0 < t \leq T_1 \tag{9.11}$$

[6] This approach involves the specification of a particular form of firm conduct leading to competitive interaction. Studies in the new empirical industrial organization tradition instead estimate firm conduct rather than making an *a priori* assumption (see, e.g., Kadiyali et al., 1996 for a discussion of this approach).

Table 9.3 Normative models in a competitive setting

	(1) Eliashberg and Jeuland (1986)	(2) Padmanabhan and Bass (1993)	(3) Gabszewicz et al. (1992)	(4) Dockner and Jorgensen (1988)	(5) Rao and Bass (1985)
1. Product characteristics	Durable	Durable, successive generations of innovation introduced by different firms	Nondurable, experience goods for which consumers learn by using product (undifferentiated)	General model, but primary focus on durables	Dynamic industry price and market share paths in an undifferentiated oligopoly, with cost learning
2. Customer behavior/demand:					
(a) Demand drivers/ sources of demand dynamics	Cumulative industry sales (saturation effect), own and cross price	1st gen: cumulative firm sales (saturation effect), own price; 2nd gen.: cumulative firm sales and own price, plus fraction of 1st gen. demand	Distribution of willingness to learn, prices	Cumulative firm/ industry sales' prices (general specification of diffusion model; special cases analyzed)	Cumulative sales (diffusion and saturation effects), industry price
(b) Heterogeneity	No (aggregate-level specification)	No (aggregate-level specification)	Heterogeneity in willingness to learn (to use product)	No (aggregate-level specification)	No (aggregate-level specification)
(c) Uncertainty/ learning?	No	No	Yes: learning through experience	No	Aggregate
(d) Strategic customers?	No	No	No	No	No

3. Firm/industry:					
(a) Experience curve effects?	No	No	No	Yes	Yes
(b) Uncertainty/ learning?	'Surprised' monopolist contrasted with correct anticipation of entry	No	No	No	No
(c) Competitive setting	Monopoly period followed by duopoly	Monopoly period followed by duopoly	Monopoly period followed by duopoly	Oligopoly	Oligopoly
(d) Decision variable(s)	Price	Price	Price	Price	Quantity
(e) Type of equilibrium	Nash, open-loop	Nash, open-loop	Nash (Bertrand competition)	Nash, open-loop	Nash, open-loop
4. Key results/pricing implications	• First entrant prices *drop* at point of follower's entry • First entrant who correctly anticipates second entry (a) prices *higher* and decreases prices more gradually than if it were myopic, and (b) prices *lower* than if it did not anticipate the second entry	• 1st gen. price *lower* than for integrated firm producing both generations in monopoly • 1st gen. price *drops* at 2nd gen. entry • After 2nd gen. entry, 1st gen. price *higher* than for integrated firm • 2nd gen. price *equal* to that for integrated firm	• In case of brand-specific learning, pioneer prices *low* in monopoly period; both firms price *above* marginal cost in duopoly period • In case of category-level learning, pioneer chooses monopoly price in first period; both firms forced to price at marginal cost in second period	• Prices may initially *increase* if diffusion effect is sufficiently strong, then *decrease* later • When demand is adversely affected by cumulative sales of competitors, change in slope of price path from positive to negative will tend to be *delayed* • Stronger impact of competition will *lower* prices	• Industry prices will *increase* when diffusion effect is dominant and *decrease* when saturation effect is dominant • Lower-cost firm will have higher market share (with common industry prices) • Given cost-side learning, high-cost firm will produce more to reduce (or even reverse) cost disadvantage

Table 9.3 (continued)

	(6) Dockner and Gaundersdorfer (1996)	(7) Baldauf et al. (2000)	(8) Dockner and Fruchter (2004)	(9) Chatterjee and Crosbie (1999)	(10) Wernerfelt (1985)
1. Product characteristics	Durable goods (with demand governed by saturation effects)	Durable goods (with demand governed by saturation effects)	Durable goods (with demand governed by saturation effects)	Durable goods (of different quality across firms)	Nondurable, experience goods for which consumers learn by using product
2. Customer behavior/demand:					
(a) Demand drivers/ sources of demand dynamics	Cumulative industry sales (saturation effect) and prices for both firms	Cumulative industry sales (saturation effect) and prices for both firms	Cumulative industry sales (saturation effect) and prices for both firms	Distribution of reservation prices, prices, effect of customer foresight	Market shares of both firms, price difference (also informative and persuasive advertising in extended model)
(b) Heterogeneity	No (aggregate-level specification)	No (aggregate-level specification)	No (aggregate-level specification)	Yes – reservation prices	No (aggregate-level specification)
(c) Uncertainty/ learning?	No	No	No	No	Yes – learning through experience
(d) Strategic customers?	No	No	No	Yes – perfect foresight	No
3. Firm/industry:					
(a) Experience curve effects?	No	No	No	No	Yes
(b) Uncertainty/ learning?	No	Yes – 2nd period demand uncertain	No	No	No
(c) Competitive setting	Duopoly	Duopoly	Oligopoly	Duopoly	Duopoly
(d) Decision variable(s)	Price	Price	Price	Price	Price, also advertising
(e) Type of equilibrium	Nash, closed-loop	Nash, closed-loop (and open-loop)	Nash, closed-loop	Subgame-perfect (closed-loop)	Nash, open-loop

4. Key results/pricing implications	• Closed-loop equilibrium price *higher* than myopic price; *drops* toward myopic price as discount rate increases • Prices *decrease* as degree of competition between firms increases	• Prices under closed-loop strategies are *lower* than open-loop strategies. In both cases, prices *decline* over time and are *higher* than myopic prices • When firms use debt financing, the 1st and 2nd period prices are *lower* and *higher*, respectively, relative to the no-debt case	• Closed-loop equilibrium prices are *declining* over time; higher the speed of diffusion, the *lower* the prices (in monopoly case, price independent of speed of diffusion) • Prices *decrease* as number of firms in oligopoly increases	• Prices *decline* over time; customer foresight and competition both act to *lower* prices and *reduce* the rate of decline • Superior performance provides firm with powerful competitive advantage in presence of customer foresight	• Over life cycle, prices generally first decline and then increase
	(11) Wernerfelt (1986)	(12) Chintagunta et al. (1993)	(13) Chintagunta and Rao (1996)	(14) Bergemann and Välimäki (1997)	(15) Kalra et al. (1998)
1. Product characteristics	Nondurable, experience goods for which consumers learn by using product	Nondurable, experience goods	Nondurable, experience goods	Nondurable, experience goods – one established brand of known value and one new entrant of uncertain value	Nondurable, experience goods – one established brand of known quality and one new entrant of uncertain quality
2. Customer behavior/demand:					
(a) Demand drivers/ sources of demand dynamics	Market shares, prices (general specification)	Customer preference, consumption experience, advertising, prices	Customer preference, consumption experience, advertising, prices	Distribution of customer valuations, prices	Distribution of customer valuations, prices

Table 9.3 (continued)

	(11) Wernerfelt (1986)	(12) Chintagunta et al. (1993)	(13) Chintagunta and Rao (1996)	(14) Bergemann and Välimäki (1997)	(15) Kalra et al. (1998)
(b) Heterogeneity	No (aggregate-level specification)	Yes – preferences	Yes – price sensitivity (at segment level)	Yes – preference (Hotelling)	Yes – valuation of quality
(c) Uncertainty/ learning?	Brand loyalty through experience	Preferences adjusted through consumption experience	Preferences adjusted through consumption experience	Yes – value of new brand	Yes – quality of new brand
(d) Strategic customers?	No	No	No	Yes	Yes
3. Firm/industry:					
(a) Experience curve effects?	Yes (on variable and fixed costs)	No	No	No	No
(b) Uncertainty/ learning?	No	No	No	Yes – value of new brand (symmetric information between firms and customers)	No
(c) Competitive setting	Oligopoly	Duopoly	Duopoly	Duopoly, with one established and one new brand	Duopoly, with one established and one new brand
(d) Decision variable(s)	Price	Price, advertising	Price	Price	Price
(e) Type of equilibrium	Nash, open-loop	Nash open-loop	Nash open-loop	Markov-perfect equilibrium (closed-loop)	Sequential equilibrium

4. Key results/pricing implications	• Prices *decline* in presence of variable cost learning and *increase* over time in presence of demand-side learning (loyalty) and fixed-cost learning	• For identical firms, prices *increase* over time (advertising declines) • If one firm enjoys higher consumer experience, other firm will price *lower* and advertise more to close gap	• At steady state, the more preferred brand charges the *higher* price	• The expected price path of new product *increases* over time, first at an increasing then at a decreasing rate • The expected price path of the incumbent *decreases* over time, first at a decreasing and then at an increasing rate	• Under certain conditions, incumbent prices higher (than in full-information case) in first period before dropping prices in second period after entrant's quality is known • Entrant selects same initial price, whether high or low quality (signal-jamming equilibrium)

$$\text{Duopoly: } dN_1(t)/dt = [\overline{N} - (N_1(t) + N_2(t))]\alpha_1[1 - kp_i(t) + \gamma(p_j(t) - p_i(t))],$$

$$i, j = 1, 2; j \neq i, T_1 < t \leq T_2 \tag{9.12}$$

where $N_i(t)$ and $p_i(t)$ are firm i's cumulative sales and price at time t, and $\overline{N}$ is the potential market size. The firms' objective is to maximize (undiscounted) profits over the entire planning horizon (including both monopoly and duopoly periods for the pioneer), assuming constant marginal cost (no cost-side learning). The open-loop equilibrium analysis shows that the prices for both firms decline monotonically, as expected, given that the dynamics are driven by saturation effects alone. The following results are interesting:

- In the presence of cross-price effects ($\gamma > 0$), there is a discrete drop in the pioneer's price at T_1, when it loses its monopoly status; greater substitutability (larger γ) implies a larger drop.
- The monopolist who correctly anticipates entry at T_1:
  - prices higher, and lowers prices less rapidly, than if he had been myopic because he accounts for the dynamic effects of saturation (greater current sales reduce future sales);
  - prices lower than if he (wrongly) assumes no competitive entry when setting its policy at $t = 0$, to reduce the potential market for the competitor via rapid market penetration.

Padmanabhan and Bass (1993; Table 9.3(2)) contrast the 'integrated monopolist' discussed in Section 2.4 with the case of separate firms introducing the first- and second-generation products (G1 and G2), for example, under technological leapfrogging by the second firm. The authors compare the pricing implications under the two scenarios (integrated and independent), using the following specific demand models in place of the more general forms (9.9) and (9.10):

$$\text{G1: } dN_1(t)/(dt = (1 - \theta)(\overline{N}_1 - N_1)(t))\exp(-k_1p_1(t)), \text{ and} \tag{9.13}$$

$$\text{G2: } dN_2(t)/dt = [\theta(\overline{N}_1 - N_1(t))\exp(-k_1p_1(t)) + (\overline{N}_2 - N_2(t))]\exp(-k_2p_2(t)) \tag{9.14}$$

where, as before, $N_1(t)$,$N_2(t)$ are the cumulative G1 and G2 sales, $p_1(t)$,$p_2(t)$ are the G1 and G2 prices, and θ is the fraction of G1 sales switching to G2 ($\theta = 0$ before G2 introduction, and a constant thereafter). $\overline{N}_1$ and $\overline{N}_2$ are the market potentials for G1 and G2.

Note that the demand interrelationship between G1 and G2 in the second period is quite different from that between the competing products in Eliashberg and Jeuland's model, where the interrelationship is more symmetric, reflecting the different scenarios modeled. Padmanabhan and Bass focus on successive generations, with demand for G2 coming from cannibalization of G1 sales and from the independent potential market for G2. The demand for G1 is independent of the G2 price. However, like Eliashberg and Jeuland, Padmanabhan and Bass assume only saturation effects. Under these assumptions, the pricing implications for the independent (competitive) versus integrated cases are as follows:

- G1 and G2 prices decline monotonically over time in both integrated and independent cases, given that the demand dynamics are driven by saturation effects.
- Prior to G2 entry, the G1 price is lower at any point in time in the competitive case, since the first entrant prefers to reduce the potential G1 market remaining when G2 enters.
- At the time of G2's entry, the G1price drops immediately in both cases.
- After G2's entry, the G1 price is higher in the competitive case, the opposite of the situation before G2 entry; in this model, the fraction of G1 sales cannibalized by G2 is a constant (θ).
- The G2 price is the same in both cases; the G1 price has no impact on the optimal G2 price.

Nondurable goods model In contrast to the above durable goods models with saturation driving demand dynamics, Gabszewicz et al. (1992; Table 9.3(3)) analyze a two-period model for a nondurable, with brand loyalty resulting from consumer learning-by-using. The products from the pioneer and follower are perfectly substitutable, although loyalty serves as a barrier to switching. Consumers are heterogeneous in their willingness to learn how to use the new product. The product must be consumed in the period purchased, and cannot be stored. At the end of the first period, those who bought the product have learned to use it. The authors compare the implications of two cases – brand-specific versus category-level learning:

- If the learning is brand specific, the pioneer uses a low introductory price in the monopoly period. In the second (duopoly) period, both brands price above marginal cost, despite being perfect substitutes; the pioneer brand has the higher price and the higher profits.
- If the learning is at the category level, the pioneer prices at the myopic monopoly price in Period 1 since there is no brand-specific advantage. Without brand loyalty, both firms are forced to price at marginal cost in Period 2, under Bertrand competition.

Thus brand-specific learning provides the pioneer with a first-mover advantage but also softens subsequent price competition via market segmentation, leaving even the follower better off than under category-level learning. The pioneer builds a sustainable competitive advantage via a loyal customer base by pricing low in the monopoly period. (In this model, the pioneer actually raises his price in the duopoly period over the monopoly period.)

3.3 Models incorporating competition against incumbent firms

Durable goods models: dynamics induced by diffusion and/or saturation effects Dockner and Jorgensen (1988; Table 9.3(4)) develop an oligopolistic extension of the Kalish (1983) model discussed in Section 2.1, starting with the following general demand model:

$$dN_i/dt = f_1(N_1(t), N_1(t), N_2(t), \ldots, N_n(t); p_1(t), p_2(t), \ldots, p_n(t)), i = 1, 2, \ldots, n \tag{9.15}$$

where $N_i(t)$ and $p_i(t)$ are the cumulative sales and price for firm i, respectively. They analyze special cases of this general model. In general, the qualitative implications for price trajectories are consistent with the results in Kalish (1983). Case 1 considers price effects only, with dynamics only due to cost-side learning – with positive discount rates, optimal prices decline over time. Case 2 considers own and competitive prices as well as own cumulative sales N_i (but not cumulative industry sales), in a multiplicatively separable formulation:

$$dN_i/dt = f_i(N_i(t)) \cdot h_i(p_1(t), p_2(t), \ldots, p_n(t)), \quad i = 1, 2, \ldots, n \tag{9.16}$$

In this case, for a zero discount factor, equilibrium prices increase (decrease) over time if df_i/dN_i is positive (negative) for all i. As discussed earlier, df_i/dN_i is likely to be positive early in the life cycle (when the diffusion effect is dominant), and negative later when saturation drives the dynamics. Case 3 is similar to (9.16) except that demand is a function of cumulative industry sales $N = \sum_i N_i$ rather than firm-level cumulative sales N_i. Assuming a linear price effect, $h_i = a_i - b_i p_i + \sum_i \gamma_{ij}(p_i - p_j)$ and ignoring discounting and cost learning, equilibrium prices increase (decrease) over time if df_i/dN is positive (negative). Finally, Case 4 considers a duopoly, with demand a function of own and competitive cumulative sales but only own price:

$$dN_i/dt = f_i(N_i(t), N_j(t)) \cdot h_i(p_i(t)), \quad i, j = 1, 2; i \neq j \tag{9.17}$$

Again ignoring discounting and experience effects, equilibrium prices increase (decrease) over time if df_i/dN_i is positive (negative), though the change in slope of the price path (from positive to negative) occurs after the change in sign of df_i/dN_i (from positive to negative) if df_i/dN_j is nonzero. The intuition is that there is a greater incentive to penetrate the market to reduce the potential market for the competitors $(df_i/dN_j < 0)$. In summary, the key implications of Dockner and Jorgensen's competitive extension of Kalish's (1983) model are as follows:

- Equilibrium prices tend to increase over time early in the life cycle when the effect of cumulative adopters on demand is positive. Later in the life cycle, equilibrium prices should tend to decline when the effect of cumulative adopters on demand is negative. This robust result holds across a variety of the competitive model variations considered, and is consistent with Kalish's results in the monopoly case.
- When a firm's demand is adversely affected by the cumulative sales of competing brands, the change in the slope of the price path from positive to negative will tend to be delayed.
- In general, the stronger the impact of competition (e.g. a larger cross-price effect on demand), the greater the downward pressure on prices.

In contrast to the models reviewed so far, Rao and Bass (1985; Table 9.3(5)) consider quantity (output) rather than price as the decision variable, in an undifferentiated oligopoly (so that there is a common industry price). The objective is to examine price and market share dynamics in the presence of demand- and cost-side dynamics. The common

industry price is a function of cumulative and current industry sales. The authors consider three special cases that isolate the three sources of dynamics in turn: saturation, diffusion and cost-side learning. While the industry price dynamics are in line with other models – price declines (increases) monotonically under a saturation (diffusion) effect alone, and also declines under cost-side learning alone – the analysis reveals interesting results for market share dynamics. Under demand-side dynamics (diffusion and saturation), a lower-cost firm will always have a higher market share than a higher-cost firm. Given cost-side learning, a higher-cost firm is more aggressive than a lower-cost firm in closing the gap in market share over time. Indeed, market share order reversals can occur in cases where the higher-cost firm might find it optimal to produce more than a lower-cost competitor.

Rao and Bass provide an empirical analysis of price dynamics in the semiconductor components industry that generally supports the theoretical results. The assumption of output as the decision variable in an undifferentiated market may be reasonable for industries with essentially commodity-type products (such as certain types of semiconductor components).

Models considering closed-loop equilibria Dockner and Gaundersdorfer (1996; Table 9.3(6)) analyze the properties of closed-loop equilibria for a durable goods duopoly market, considering saturation effects only and an infinite planning horizon. The closed-loop equilibrium price is higher than the myopic price, and drops toward the latter as the discount rate increases. Also, as expected, prices decrease as the products become more substitutable.[7] However, the analysis does not compare open-loop and closed-loop strategies.

Baldauf et al. (2000; Table 9.3(7)) employ a two-period duopoly model with saturation effects to contrast open-loop and closed-loop strategies. They find that:

- When firms choose closed-loop strategies, optimal prices in each period are lower than corresponding open-loop prices. In both cases, prices decline over time and are higher in each period than the corresponding myopic prices.

Closed-loop strategies capture strategic competitive interaction, resulting, in this instance, in lower prices. Next, Baldauf et al. consider the implications of debt financing. Uncertainty is introduced in the second-period demand via a random disturbance term in market potential. The firms' objective is to maximize the expected equity value, concentrating on those states of nature in which there will be no bankruptcy. In this situation, long-term debt has a significant impact:

- When firms use debt financing, second period prices are higher (to avoid possible bankruptcy) while first period prices are lower (to compensate for higher second period prices) relative to their levels in the case of no debt financing.

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[7] The degree of substitution is captured by the γ parameter, as in Eliashberg and Jeuland (1986) – see (9.14).

Dockner and Fruchter (2004; Table 9.3(8)) investigate the combined effect of the speed of diffusion and competition, using the following demand specification:[8]

$$dN_i(t)/dt = \left[\overline{N} - \sum_{i=1}^{n} N_i(t)\right]\left[a - bp_i(t) + \gamma \sum_{\substack{j=1 \\ j \neq i}}^{n} (p_j(t) - p_i(t))\right], i = 1, \ldots, n \tag{9.18}$$

where the notations are as defined earlier. The speed of diffusion is defined as the percentage increase in the number of adopters corresponding to a 1 percent decrease in the time remaining in the product life cycle (an elasticity-like measure). The key implications are:

- Equilibrium prices decline over time. Given competition, the higher the speed of diffusion (i.e. shorter the life cycle), the lower the prices. In contrast, in a monopoly, the optimal price path is independent of the speed of diffusion.
- The prices decrease as the number of competitors in the oligopoly increases.

Models considering strategic customers with price expectations Chatterjee and Crosbie (1999; Table 9.3(9)) extend Besanko and Winston's (1990) model, discussed in Section 2.3, to a duopoly market, in which firms may sell products differentiated by quality. Customers are rational, with perfect foresight, and heterogeneous in their reservation prices. A subgame-perfect (closed-loop) equilibrium is sought in a discrete time framework. The results, derived partly analytically and partly via numerical simulation, have the following policy implications:

- Equilibrium prices decline over time as customers adopt the durable and leave the market in descending order of their valuations. Customer foresight and competition both lower prices and flatten the declining price path.
- Superior quality can provide a firm with a powerful, even dominant, competitive advantage relative to the case of myopic customers. A strong quality advantage can counteract a competitor's potential advantage from early brand introduction or lower marginal cost.

Nondurable goods models We next review four models that focus on nondurable products for which there is demand-side learning on account of consumption experience. Wernerfelt (1985; Table 9.3(10)) investigates price and market share dynamics over the life cycle in a duopoly, given scale economies and cost-side learning. The demand-side dynamics are modeled as follows. First, the rate of change of market share is proportional to the market shares of the two brands, the price difference, and a term that declines over time to reflect increasing brand loyalty. Next, the rate of change of individual-level consumption decreases in both price and the current consumption level. Finally, a financial constraint is imposed, requiring that some fraction of the funding needed for growth must be generated internally (based on prescriptions from the Boston Consulting Group). Wernerfelt's open-loop equilibrium analysis shows that:

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[8] This model is a special form of Case 3 in Dockner and Jorgensen (1988), with dynamics from saturation effects.

- Prices first decline and then increase; the larger firm's market share first grows, then declines.

The implications for the slope of the price path over the life cycle are the opposite of those implied by Dockner and Jorgensen's (1988) durable goods model based on diffusion and saturation effects, given the very different demand dynamics in Wernerfelt's model for frequently purchased products. In the case of durables with a finite market, saturation eventually dominates demand-side learning, whereas in Wernerfelt's model, demand-side learning (lowering price sensitivity) continues to grow without the constraint of saturation.

Wernerfelt's (1986) model (Table 9.3(11)) focuses on the implications of experience curves and brand loyalty for pricing policy in an oligopoly. Both fixed and variable costs decline owing to learning and exogenous technical progress. As in Wernerfelt (1985), the market share dynamics depend on current shares, prices and brand loyalty. The implications are that prices should decrease over time if discount rates are high and exogenous declines in variable costs are steep, but increase if fixed costs decline with learning and consumers are brand loyal.

Chintagunta et al. (1993; Table 9.3(12)) analyze dynamic pricing and advertising strategies for a nondurable experience good in a duopoly. Individual-level consumer choice is based on an ideal point preference model. Brand share is obtained by aggregating over consumers, allowing for heterogeneity. Consumers learn about a brand with each successive purchase. The accumulated brand consumption experience obeys Nerlove and Arrow (1962):

$$dG_i(t)/dt = S_i(t) - \delta G_i(t), \quad G_i(0) = G_{i0}, \quad i = 1, 2 \tag{9.19}$$

where $G_i(t)$ and $S_i(t)$ are firm i's stock of accumulated consumption experience (goodwill) and sales, and δ is the goodwill decay factor. A brand's perceptual location depends on the function of current advertising effort and the accumulated consumption experience, so that higher levels of either imply greater brand preference. The key results, derived via numerical simulation, are:

- If firms are identical, prices increase over time (while advertising decreases).
- If one firm enjoys higher initial consumption experience by being the incumbent, then the other firm will initially market more aggressively by pricing lower (and advertising higher) than the incumbent. Over time, the price and advertising levels for the two brands converge.

In a related paper, Chintagunta and Rao (1996; Table 9.3(13)) develop a duopoly model for nondurable experience goods, with aggregate-level preference evolving according to the Nerlove–Arrow model, similar to the accumulated consumption experience in Chintagunta et al. (1993). At steady state, the more preferred brand charges the higher price. The authors show that managers who are myopic or who ignore customer heterogeneity make suboptimal pricing decisions. An empirical example demonstrates how the model may be estimated (and steady-state price predictions obtained) from longitudinal purchase data.

Competition against an established nondurable Bergemann and Välimäki (1997; Table 9.3(14)) consider the case of a firm introducing a new, differentiated, product to a market for a nondurable experience good currently served by an established firm with a product whose performance is well known.[9] However, the performance of the new product is initially uncertain to customers as well as to the firms. This uncertainty can be resolved only by learning through actual purchases of the second product. Beliefs of product performance are updated gradually in a Bayesian manner. The authors derive the Markov-perfect equilibrium[10] of the infinite horizon differential game, with the following implications, if the new product is of truly high quality:

- The expected price path of the new product is strictly increasing over time, first at an increasing and then at a decreasing rate (i.e. in an S-shaped pattern), while that of of the established product is strictly decreasing, first at a decreasing and then at an increasing rate.

The uncertainty serves to soften competition and increase profits. The incumbent actually values information on new product performance more than the entrant does. Since such information is only available from new product sales, the incentives produce the dynamics noted above.

Kalra et al. (1998; Table 9.3(15)) consider a somewhat similar scenario – an established incumbent and a new entrant whose product is of uncertain quality – to examine whether there is a rationale for the incumbent to react slowly to the entrant as often observed in practice, when the expected response (under full information) would be an immediate price cut. Consumers are initially uncertain about the entrant's quality, and the true quality is revealed over time. Unlike in Bergemann and Välimäki, both firms know the true quality. The analysis, using the sequential equilibrium concept (Krebs and Wilson, 1982) in a two-period model, shows that:

- There are conditions under which the incumbent prices higher than the full-information price to effectively jam the entrant's ability to signal quality via its price. In this signal-jamming equilibrium, the low-quality and high-quality entrants select the same price. The incumbent's price gradually declines to the full-information level as consumers learn about the entrant's true quality.

Thus, whereas a monopolist may use price as a signal of quality (see Section 2.3), a later entrant may not have the ability to do so because of signal-jamming by the incumbent. This is also consistent with the often-observed practice of a delayed or gradual incumbent response. Kalra et al. also provide experimental validity for the premise underlying their result.

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[9] For other work by the same authors examining implications for strategic pricing in the presence of two-sided learning, see Bergeman and Välimäki (1996, 2000).

[10] See Maskin and Tirole (2001) for a discussion of Markov-perfect equilibrium.

3.4 Normative models in a competitive setting: summary of implications

We conclude this section by summarizing the main implications for new product pricing strategy in a competitive setting, relative to the implications in a monopolistic setting (Section 2.5).

- *General effect of competition* In general, the stronger the effect of competition (for example, a larger cross-price effect), the lower the prices, all else equal.
- *Anticipating entry in a durable goods market with saturation effect* Prior to the competitor's entry, the incumbent monopolist's optimal strategy is to price higher and then reduce prices less rapidly over time than the myopic optimum, but price lower than if he does not account for competitive entry. Also, at the point of entry, the incumbent's price drops, with the magnitude depending on the strength of the cross-price effect.
- *Anticipating entry in a nondurable goods market with learning-by-using* If the learning by customers is mainly brand-specific (rather than at the category level), the pioneer prices below the myopic monopoly price prior to the competitor's entry.
- *Durable goods oligopoly* When a firm's demand is adversely affected by the cumulative sales of competitors (owing to saturation), there is greater incentive to use penetration pricing early relative to the monopoly situation – thus early prices will be lower and the change of slope of the price path from positive to negative will be delayed.
- *Open-loop versus closed-loop strategies for durable goods market with saturation* When firms adapt to the evolving state of the system over the planning horizon rather than committing to their strategy at the start of the planning horizon, prices in each period are lower.
- *Strategic customers with perfect foresight in a durable goods market* Both customer foresight and competition lower prices and make the price decline more gradual.
- *Nondurable goods duopoly with learning-by-using* Prices may first decline and then increase, or else increase monotonically over time; if one firm enjoys greater consumption experience initially (e.g. as the incumbent), the other firm will be more aggressive in its marketing, including charging lower prices, to close the gap between the firms.
- *Competitive reaction to a new entrant when the entrant's quality is uncertain to customers* Under certain conditions, the incumbent prices higher than the full-information duopoly price to effectively prevent the entrant from signaling quality to uncertain customers.

4. Setting new product prices in practice

In this section, we briefly discuss some tools and approaches that managers may apply to determine actual pricing policy for new products. A more detailed review of this topic is beyond the scope of this chapter; related issues are covered elsewhere in this volume.

4.1 Conjoint-based methods

Conjoint analysis (Green and Srinivasan, 1978, 1990) provides a popular and widely used methodological tool for assessing customers' willingness to pay for (possibly hypothetical) new products (Jedidi and Zhang, 2002). In particular, conjoint-based methods

for optimal pricing (preferably as part of an overall optimization methodology including product design) have been developed and applied (Green et al., 1981; Kohli and Mahajan, 1991; see also Dolan and Simon, 1996).[11] For methodological approaches based on information directly obtained from customers (or from secondary data) to estimate new product demand as a function of price and other demand-drivers, we refer readers to the chapters in this volume on measurement of reservation prices at the disaggregate level (Jedidi and Jagpal, Chapter 2) and demand estimation at a more aggregate level (Liu et al., Chapter 3).

4.2 Field experimentation

In situations in which it is important to track demand dynamics over time, an extended field experiment allows for estimation of a demand model that comes close to capturing reality. An example of such research is the study by Danaher (2002) involving a field experiment to derive a revenue-maximizing pricing strategy for new subscription services (applied to cellular phone market). The study also provides measures of the impact of access and usage prices on volume of usage and customer retention. In the experiment, a panel of homes was recruited to try a new cellular phone service over a year-long period. Both access and usage prices were manipulated systematically across groups within the panel. The model for usage and attrition was developed to fit the data from the experiment while also having the flexibility to describe a subscription service market that is closer to reality than the market in the experiment. It generalizes Hausman and Wise (1979) to deal with bias in the case of attrition. Unobserved heterogeneity is accommodated by employing latent segments. The specification of the revenue (or, more generally, profit) surface as a function of access and usage prices allows for the search of the optimal access and usage price levels.

Danaher's research illustrates a useful practical approach to new product pricing, using experiments that run over a sufficient length of time with manipulation of prices to be able to estimate the key demand dynamics (in this case, usage rates and attrition), in a reasonably realistic setting. In terms of broader findings, the analysis shows that access price primarily affects retention, while usage price affects usage and has an indirect effect on retention via usage (lower usage results in higher attrition).

4.3 Expert opinion/managerial judgment

Clearly, the specific product-market situation will dictate the appropriate choice of methodology for new product pricing. For example, for the pharmaceuticals industry, Woodward et al. (1998) propose a judgment-based approach that solicits experts opinions about the new product's market share under different scenarios based on prices, promotional effort and clinical benefits (as a basis for the product's value proposition and differentiation). The procedure involves a meeting among experts. A spreadsheet-based model returns the profit-maximizing price, promotional effort and value proposition (market differentiation) for each expert and for the group as a whole. The extent of

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[11] For the interested reader, Sawtooth Software's technical papers library provides a useful set of materials of all aspects of conjoint analysis (http://www.sawtoothsoftware.com/education/techpap.shtml).

disagreement among experts is used to estimate incremental profits from obtaining additional information, via (i) an additional clinical trial (to define a stronger value proposition, possibly by establishing a second clinical indication) and (ii) a demand survey (to better estimate potential sales at different price points).

In summary, customer measurement tools (such as conjoint analysis), experiments (preferably in field settings), and expert opinion/managerial judgment-based approaches (Little, 1970, 2004), have been – and can be – used, possibly in combination, to determine pricing policy for a new product.

5. Conclusion

This chapter has attempted to organize and review the literature on new product pricing, with a primary focus on normative models taking a dynamic perspective. Such a perspective is essential in the new product context, given the underlying demand- and supply-side dynamics and the need to take a long-term, strategic, view in setting pricing policy. Along with these dynamics, the high levels of uncertainty (for firms and customers alike) make the strategic new product pricing decision particularly complex and challenging. We have distilled from our review of normative models the key implications for new product pricing, under various situations. These implications are intended to provide (i) theoretical insights into the drivers of dynamic pricing policy for new products and services, (ii) directional guidance for new product pricing decisions in practice, and (iii) directions for empirical research to test these results.

Given the multiple sources of dynamics and uncertainty, normative models have typically focused on some subset of all the situational factors that might exist in practice, in order to be tractable. Isolating the different effects helps in understanding their individual impact on the price path. However, being abstractions of reality, these models are limited as practical tools for new product pricing. On the other hand, the new product pricing tools available, briefly discussed in Section 4, are primarily helpful for setting short-term prices rather than a dynamic long-term pricing policy, which is what managers really need. Our review and discussion suggests several areas that offer opportunities for future research. Some avenues are discussed below.

5.1 Normative models: possible extensions

Dynamic models incorporating future expectations, successive generations, and current and future competition Today's business environment – characterized by shorter product life cycles, rapidly evolving demand- and supply-side dynamics (including customer tastes, technology and competition), and increasingly sophisticated customers – poses a real challenge for modelers, who must focus on these key drivers simultaneously to obtain managerially relevant pricing implications. Even with better analytical tools, the tradeoff between analytical tractability and richness must be recognized. Numerical methods would typically need to be used in conjunction with analytical approaches in order to derive meaningful results in these circumstances.

Multiple decision variables It is clearly simplistic to focus on price alone as the decision variable. While some dynamic models include additional marketing variables (typically, advertising), real-world new product strategy involves decisions across

functional areas. In this regard, the model by Huang et al.(2007) reviewed in Section 2.1 represents an encouraging start, albeit in a monopolistic setting. Again, the tradeoff between tractability and richness (and the use of numerical methods) becomes a germane issue.

5.2 Decision support systems

As observed earlier, the existing tools to support new product pricing decisions are limited in their ability to provide recommendations on dynamic pricing policy. There is an opportunity for developing managerial decision support systems incorporating dynamic models that can be calibrated via managerial judgment, historical data on analogous products, experimentation, or (ideally) some combination thereof to provide dynamic pricing strategy recommendations.

5.3 Nontraditional pricing schemes and other recent advances in pricing

The unique characteristics of services has prompted pricing schemes that include advanced pricing, use-based pricing and pricing for yield management. These topics have received recent attention and are covered in chapters in this volume by Shoemaker and Mattila (Chapter 25) on services, Xie and Shugan (Chapter 21) on advanced pricing, Kimes (Chapter 22) on yield management, and Iyengar and Gupta (Chapter 16) on nonlinear pricing. Further, prompted in part by recent technological advances (including the advent of the Internet), customized pricing of goods and services is now a viable option, prompting increasing use of auctions (and reverse auctions), and pricing to maximize customer lifetime value. Again, these topics are discussed in chapters by Park and Wang (Chapter 19) on mechanisms facilitated by the Internet (including 'name your own price' and auctions) and Zhang (Chapter 14 on price customization).

While these newer pricing topics have generated considerable research interest, there has been little work so far in the context of new products. This is clearly an important and fertile area for research, considering the unique challenges posed by new products, as discussed.

5.4 Takeoff of really new products

An example of an interesting research issue in the new product pricing domain is Golder and Tellis's (1997) study of takeoff in sales of new household consumer durables. The authors argue that the traditional new product diffusion models do not capture the reality of the abrupt sales 'takeoff' for major innovations, at which point sales jump fourfold (or greater). They find that, for 16 post-World War II consumer durable categories, the price at takeoff was 63 percent of the introductory price, on average; furthermore, the takeoff often occurs at specific price points, e.g. $1000, $500, or $100. Also, not surprisingly, the time to takeoff has been decreasing, from 18 years for categories introduced before World War II to six years for those introduced afterwards.

The phenomenon of sales takeoff warrants further attention, given the increasing number of new product introductions, particularly in the technology sector. In particular, the role of strategic pricing (and psychologically important price points, as suggested by Golder and Tellis's findings) in determining new product takeoff is a promising topic for research.

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10 Product line pricing

Yuxin Chen

Abstract

A firm in modern economy is more likely to sell a line of products than a single product. Product line pricing is a challenging marketing mix decision as products in a line demonstrate complicated demand and cost interdependence. In the last three decades researchers from different disciplines have made significant progress in addressing various issues relating to the topic of product line pricing. In this chapter, I discuss the literature on product line pricing with the focus on recent research development.

The discussion starts with a general framework of the product line pricing problem and a brief description of the decision support models for product line pricing. It is then followed with extensive discussions on the pricing of vertically differentiated product lines and the pricing of horizontally differentiated product lines respectively. Finally, I conclude the chapter with a discussion on future research directions.

1. Introduction

A firm in modern economy typically sells a line of products rather than a single product. For example, cars are offered with different powers, yogurts are offered with different flavors, online shopping is offered with different delivery options, and wireless phone service is offered with different plans. This chapter reviews the academic research on product line pricing. Its purpose is to provide a comprehensive discussion on the topic with both the experienced and new researchers as the intended audience. I shall focus on recent research development in this area. Good reviews on the early literature on this topic can be found in Rao (1984, 1993).

To be more precise about the scope of this review, I define a product line as a set of products or services sold by a firm that provide similar functionalities and serve similar needs and wants of customers. This definition sets the topic of product line pricing apart from the more general topic of multi-product pricing. For example, research on bundle pricing, razor-and-blade pricing, and loss-leader pricing in the context of retail assortment management is beyond the scope of this review according to the above definition of a product line.

In addition, to avoid the potential overlap with other chapters in this *Handbook*, I exclude the following topics from this review, even though they can be somewhat related to product line pricing: pricing multiple generations of products, pricing new products with the existence of used goods market, retailer's pricing of a category of products consisting of national and private brands, and quantity discounts. However, some overlap will still occur. This is often inevitable and even desirable because it can be beneficial to look at the same issue from different perspectives. For example, the pricing of different delivery options by an online retailer can be viewed as a problem of product line pricing but also a problem of pricing services if the service aspect is emphasized. Combining the views can provide marketing managers and researchers with more comprehensive understanding on this issue.

Because this chapter contributes to a handbook of pricing research, my discussion will

concentrate on the pricing issues conditional on the configurations of product lines. The optimal design of a product line is an important topic but it is beyond the scope of this review. Nevertheless, whenever applicable, I will try to base the discussion on the optimal or equilibrium configurations of product lines as shown in the literature.

The optimal pricing decision of a product line is critically dependent on the relations of the products in the line. In general, products in a line can be vertically differentiated, horizontally differentiated, or both. A product line is vertically differentiated if products in the line are differentiated along a dimension (product attribute) in which consumers have the same preference ranking on each level. That is, all consumers prefer to have more (or less) of the attribute. Such a dimension is typically interpreted as product quality in the literature (Moorthy, 1984; Mussa and Rosen, 1978). Examples of vertically differentiated product lines include iPods with different memory capacities and printers with different speeds. A product line is horizontally differentiated if the products in the line are differentiated along dimensions in which consumers have different preference rankings due to their taste differences. Examples of such product lines include ice creams with different flavors and clothes with different colors. In practice, it is common for a product line to be vertically differentiated along some dimensions but horizontally differentiated along others. For example, a line of automobiles may be vertically differentiated on gas-mileage but horizontally differentiated on colors. In this review, I classify previous studies based on their focus on vertically differentiated or horizontally differentiated product lines and discuss the pricing issues for these two types of product lines respectively in two sections. For papers applicable to both vertically differentiated and horizontally differentiated product lines, I discuss them in either section, depending on their emphasis and main contributions.

The objective of this chapter is to provide a comprehensive review of important research developments in product line pricing. However, due to space and knowledge limitations, this review is far from exhaustive. Readers who are interested in any specific topic of product line pricing research are encouraged to conduct more extensive literature search in that area.

The rest of the chapter is organized as follows. In the next section, I present a general framework for the product line pricing problem and briefly discuss the decision support models for product line pricing. I discuss the pricing of vertically differentiated product lines in Section 3 and horizontally differentiated product lines in Section 4. Finally, I conclude the chapter in Section 5 with a discussion on future research directions.

2. A general framework for product line pricing

Assume a firm sells a product line consisting of m products. The firm's optimal pricing problem can be formulated as

$$\underset{p_1,p_2,\ldots,p_m}{\text{Max}}\ \pi = \sum_{i=1}^{m}\pi_i = \sum_{i=1}^{m} D_i(p_i, P_{-i}, P_c, X, X_c)p_i - \sum_{i=1}^{m} C_i(D_i, D_{-i}) \tag{10.1}$$

where

π is the total profit of the product line,
π_i is the profit of the ith product in the product line,
D_i is the demand of the ith product,

D_{-i} is a vector of demand of the products other than the ith product in the line,
p_i is the price of the ith product,
P_{-i} is a vector of prices of the products other than the ith product in the line,
P_c is a vector of prices of the products from competing firms,
X is a vector of the firm's marketing mix variables other than prices on all products in the line,
X_c is a vector of the marketing mix variables other than prices from competing firms, and
C_i is the cost of selling D_i units of the ith product

Equation (10.1) reveals two significant differences in pricing a product line as compared to pricing a single product. The first difference comes from the demand interdependence of the products in a line. Unlike the demand in the single-product case, the demand of product i in a line is not only a function of its own price but also a function of the prices of the other products in a line. The second difference comes from the cost interdependence of the products in a line. On the one hand, the economies of scale may reduce the production cost of each product as the number of products in a line decreases. This is because a shorter product line leads to more sales for each product in the line. On the other hand, the economies of scope may lower the cost of each product when more products are added into the product line.

Generally, demand interdependence leads to the cannibalization effect. That is, lowering the price of one product steals the demand from the other products in the line. This is because products in a line are partial substitutes, by our definition of product line. However, under some circumstances, demand among the products in a line can be complementary even though they are substitutes in functionalities. For example, a low price for a product in the line may attract consumers to the line and they may end up buying other products in the line through the 'bait and switch' mechanism (Gerstner and Hess, 1990). As another example, setting a very low price to a product in a line may increase the sales of a high-priced product in the line due to the 'compromise effect', well documented in the consumer behavior literature (Kivetz et al., 2004; Simonson and Tversky, 1992).

The presence of demand and cost interdependence for products in a product line makes the optimal pricing decision a challenging one. There are two main difficulties. First, it is hard to come up with precise specifications of the demand and cost interdependence and estimate their parameters, especially when the number of products in a line is large. Second, it is hard to simultaneously solve for the optimal prices of all products given the complexity of demand and cost interdependence.

Researchers have proposed various mathematical programming and decision support models to obtain optimal prices based on the general framework given in equation (10.1) (Chen and Hausman, 2000; Dobson and Kalish, 1988, 1993; Little and Shapiro, 1980; Reibstein and Gatignon, 1984; Urban, 1969). Generally, the decision support models on product line pricing follow a three-step procedure. The first step is to specify the functional forms of demand and cost. The second step is to estimate parameters in the demand and cost functions. The data source can be sales records, conjoint analysis output and operation/production records. Finally, the third step is to solve the optimization problem mathematically. Given the challenging nature of the product line pricing problem,

typically a number of simplifying assumptions have to be imposed in the specifications of demand and cost functions, and heuristic algorithms have to be used in optimization. Some commonly adopted simplifying assumptions include (1) ignoring reactions from the competitors and (2) ignoring interactions between prices and other marketing mix variables. In addition, cost interdependence tends to be ignored or modeled in a less sophisticated fashion than demand interdependence in those models. The primary reason, as stated in Dobson and Kalish (1993, p. 171), is that '(t)he cost structure of a firm can in many cases be very complicated and hard to measure'.

Moreover, the optimization problem as formulated in equation (10.1) is itself a simplified version of the product line pricing problem in general. Two important considerations are ignored in equation (10.1). First, the unit price of each product is assumed to be independent from the number of units purchased. Thus the practice of nonlinear pricing is not taken into account. Second, equation (10.1) is a static model and the potential intertemporal demand and cost interdependence is ignored. If we extend equation (10.1) to consider the issues of nonlinear and dynamic pricing, more complicated decision support models will be required to provide heuristic solutions to the pricing problem.

Besides mathematical programming and decision support models, researchers have also developed various analytical models on product line pricing with stylized assumptions on demand and supply. While the purpose of the decision support models is to obtain optimal prices explicitly based on demand and cost estimations, the objectives of the stylized analytical models are to identify key economic effects that influence the optimal prices and provide directional guidance for optimal product line pricing. We review the analytical models in the literature along with the empirical studies in the next two sections.

3. Pricing vertically differentiated product lines

Recall our definition of vertical differentiation from the Introduction. Examples of the dimension in this case are the power of cars, the processing speed of computers and the purity of chemicals. In the product line pricing literature, researchers typically assume that products are vertically differentiated along a single dimension and interpret such a dimension as product quality.

Firms offer vertically differentiated product lines because consumers are heterogeneous in their willingness to pay for product quality. This gives firms the incentive to conduct second-degree price discrimination, which is achieved by offering a set of products with different quality and prices. In general, there are two possible causes of demand interdependence in a vertically differentiated product line: consumer self-selection and the context effect. Consumer self-selection refers to the fact that each consumer chooses the product to buy that maximizes her net surplus. As a result, the price of one product affects the demand of other products in the line. The context effect refers to the fact that consumers' preferences toward a product can be influenced by the prices of the other products in the line. For example, Petroshius and Monroe (1987) showed that the price range of the products in a line could affect consumers' evaluation on individual products in the line. Simonson and Tversky (1992) showed that the consumers tend to avoid extreme options. Therefore, adding a high price product into a line may increase the demand of a product with a mid-level price.

While the findings from behavioral research on the context effects are interesting and important for product line pricing, most of the studies are descriptive in nature. The analytical and empirical studies on product line pricing have primarily focused on the impact of consumer self-selection. In the rest of this section, I discuss the previous research relating to consumer self-selection and product line pricing in detail.

3.1 Consumer self-selection and product line pricing: the basics

The primary consideration in the literature on pricing a vertically differentiated product line is the demand interdependence resulting from consumer self-selection. The basic modeling framework that captures the self-selection effect is as follows. Suppose a monopoly firm sells a high-quality product (H) and a low-quality product (L). Product H is designed to target consumers with high willingness to pay for quality (the H-type) and product L is designed to target consumers with low willingness to pay for quality (the L-type). If the price of H is too low, then the L-type may want to purchase product H. Similarly, if the price of L is too low, then the H-type may want to purchase product L. Generally speaking, a monopoly firm will not be able to extract consumer surplus fully because the prices of products H and L have to be set to induce consumers to 'self-select' into buying the designated products.

The above idea was formally modeled in the seminal papers by Mussa and Rosen (1978) and Moorthy (1984). While both papers assumed a monopoly seller, the former assumed a continuous distribution of consumer types and the latter assumed a discrete distribution of consumer types. The main insights of both papers are that under general conditions: (1) only the consumers with the highest valuation for quality get the efficient quality (i.e. the quality that would be chosen by a social planner for that segment) and all other segments get lower than the efficient qualities; and (2) the consumers with the lowest valuation for quality are charged with their willingness to pay for the product they buy and other consumers are charged below their willingness to pay for the products they buy. In addition, as pointed out by Verboven (1999), the pricing outcome given in Mussa and Rosen (1978) and Moorthy (1984) implies that the absolute price–cost margins increase with product quality but the percentage price–cost margins typically decrease with product quality.

To illustrate the results from Mussa and Rosen (1978) and Moorthy (1984), let us consider the following numerical example. Suppose that the market consists of one H-type consumer and one L-type consumer, and further assume that the reservation price of the H-type consumer is $3q$ and the reservation price of the L-type consumer is $2.5q$, where q is the product quality. The unit production cost is assumed to be $0.5q^2$. If a monopoly firm sells product H with quality q_H at price p_H to the H-type consumer and sells product L with quality q_L at price p_L to the L-type consumer, the profit of the firm is

$$\pi = (p_H - 0.5q_H^2) + (p_L - 0.5q_L^2) \tag{10.2}$$

If there is no demand interdependence, i.e. the H-type (L-type) consumer can only access product H (L), it will be optimal for the firm to set prices at the reservation prices of the consumers. Therefore the optimal prices are $p_H^* = 3q_H$ and $p_L^* = 2.5q_L$. Then, from (10.2), it is easy to obtain that the optimal quality levels are $q_H^* = 3$ and $q_L^* = 2.5$, and they are socially efficient. Consequently, we have $p_H^* = 9$ and $p_L^* = 6.25$ in this case.

In the situation where consumers have access to both products in the product line, each consumer can choose the one that maximizes her net surplus. In such a case, the demand of the two products becomes interdependent as a result of this consumer self-selection. Notice that the self-selection condition for the H-type consumer to choose product H over product L is

$$3q_H - p_H \geq 3q_L - p_L \tag{10.3}$$

and the condition for the L-type consumer to choose product L over product H is

$$2.5q_L - p_L \geq 2.5q_H - p_H. \tag{10.4}$$

From equations (10.3) and (10.4), we can see that the demand of each product is affected by the prices of both products. Following Moorthy (1984), it is easy to verify that (10.3) has to be binding for profit maximization but (10.4) is not binding. In addition, $p_L^*=2.5q_L$ still holds. Then, from (10.2), we can obtain that $q_H^* = 3$ and $q_L^* = 2$.[1] Consequently, $p_H^* = 8$ and $p_L^* = 5$. We can see that the consumer with the high valuation for quality still gets the efficient quality but the other consumer gets lower than the efficient quality, and the consumer with the low valuation for quality is charged at her willingness to pay for the product purchased, but the other consumer is charged below her willingness to pay for the product purchased. The above results from the numerical example demonstrate the insights from Mussa and Rosen (1978) and Moorthy (1984). It is also straightforward to verify that the absolute price–cost margins increase with product quality but the percentage price–cost margins decrease with product quality in this case as pointed out by Verboven (1999).[2]

Insights similar to those in Mussa and Rosen (1978) and Moorthy (1984) were also obtained in Maskin and Riley (1984), Katz (1984), and Oren et al. (1984). Following Mussa and Rosen (1978) and Moorthy (1984), the basic idea of pricing a vertically differentiated product line, i.e. maximizing surplus extraction with the quality-based price discrimination under the constraint imposed by consumer self-selection, has been extended into many different contexts. Detailed discussion on the related research is provided below.

3.2 Incorporating competition

A natural extension of the models in Mussa and Rosen (1978) and Moorthy (1984) is to introduce competition into the pricing problem for vertically differentiated product lines. Most papers in this area have focused on the product quality decisions and/or the decisions on the number of products to offer in product lines (Champsaur and Rochet, 1989; De Fraja, 1996; Gilbert and Matutes, 1993; Jing and Zhang, 2007; Johnson and Myatt, 2003). The basic economic force captured by those papers is the tradeoff between product differentiation to mitigate competition and product proliferation along the quality dimension to maximize the benefit from the second-degree price discrimination.

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[1] Given the parameter values in the example, it is easy to show that it is optimal to offer two products instead of one.

[2] The unit costs are 4.5 and 2 for product H and product L respectively.

As a pioneering paper in this area, Katz (1984) introduced competition by assuming that firms are horizontally differentiated, following the idea of Hotelling (1929). As expected, competition lowers firms' prices and profits. As a result, firms may offer products at different quality levels in order to avoid head-on competition.

The basic intuition behind the result of Katz (1984) can be shown using the numerical example presented in Section 3.1. Assume that there are now two firms with the same cost structure competing in the market described in that example. Further assume that each firm can potentially offer up to two products with $q_H = 3$ and $q_L = 2$. If firms simultaneously decide the number of products to offer before their pricing decisions, neither firm will offer both products in the equilibrium. This is because the Bertrand competition on any common product offered by the firms will lead to zero profit for that product for at least one of the firms. Therefore, in equilibrium one firm will offer product *H* only and the other firm will offer product *L* only.[3]

In an interesting paper by Desai (2001), the competition between firms was also modeled following Hotelling (1929) but consumers' horizontal taste differences toward the two competing firms were allowed to be different for the *H*-type and *L*-type. Desai (2001) showed that in this setup it was possible for both firms to offer efficient qualities to both consumer segments in equilibrium. The intuition behind this result is that competition lowers the price of product *H* to the *H*-type. Consequently, it reduces the incentive of the *H*-type to buy product *L*. Therefore firms may not need to lower the quality of product *L* in order to prevent the *H*-type from buying product *L*. Another innovative feature of Desai (2001) was that he allowed the possibility that the market was not fully covered. Under incomplete market coverage, he showed that even a monopoly might offer products with efficient qualities to both consumer segments. This is because the firm in his model faces a downward-sloping demand function instead of a step demand function when the market is not fully covered. As a result, the firm has the incentive to lower its price of product *H* to attract a large portion of the *H*-type. This again reduces the incentive of the *H*-type to buy product *L*.

Another interesting paper in this area is Verboven (1999). This paper studied a special type of vertically differentiated product line consisting of a base product and a premium product which was the base product plus some add-ons. This type of product line is common in the automobile industry. Under the assumption that consumers were only well informed about the base product prices, Verboven showed that the premium products could have larger percentage markups than the base products in equilibrium. This result was different from the standard result in the literature (e.g. Moorthy, 1984) and it was supported by the empirical findings of the paper.

Closely related empirical work in this area is quite scarce. A noticeable empirical research by Sudhir (2001) examined the competitive product line pricing behavior in the US auto market. He found more-competitive-than-Bertrand pricing behavior in the minicompact and subcompact segment, cooperative pricing behavior in the compact and

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[3] In this case, there is no pure strategy equilibrium in prices if firms set prices simultaneously. If firms set prices sequentially, the pure strategy equilibrium will be $p_H = 5.5$ and $p_L = 3$ when the first mover produces product *H* and the second mover produces product *L*, or $p_H=5.5$ and $p_L=2.5$ when the first mover produces product *L* and the second mover produces product *H*. We can see that the prices and profits of the firms are lower than those in the monopoly case.

midsize segment and Bertrand pricing behavior in the full-size segment. These findings can be explained by firms' ability to cooperate, which is high in the segment with high concentration, and by firms' motivation to compete, which is high in the segment for entry-level customers (the minicompact and subcompact segment) because firms try to build customer loyalty for long-run probability as those entry-level customers eventually move up to buy large cars. The findings of the paper indicate the importance of the dynamic consideration in firms' product line pricing decisions. Remarkably, such a consideration has been largely ignored in the analytical models.

3.3 Interactions with other marketing mixes

As indicated in equation (10.1), the product line pricing decision is influenced by other marketing mix variables chosen by a firm and its competitors. Recent research on pricing vertically differentiated product lines has examined the interactions of product line pricing with other marketing mixes. Villas-Boas (1998) studied a manufacturer's product line decisions when it sells through a distribution channel with a single retailer. His results show that the main conclusions from Mussa and Rosen (1978) and Moorthy (1984) are reinforced in the channel setting. In fact, the quality of the low-end product is even more distorted than in the case without the retailer. This result is obtained because double marginalization in the channel increases the price to the H-type while the L-type is always charged with the reservation price. Consequently, this increases the incentive of the H-type to buy the low-quality product. To prevent this from happening, the manufacturer has to distort the quality level of the low-end product further down.

As to the interaction between product line decision and advertising, Villas-Boas (2004) studied the situation where the function of advertising is to create product awareness. He showed that in general a monopoly firm would charge a lower price for the high-quality product and a higher price (accompanied by higher quality) for the low-quality product when advertising was costly than when it was costless. The basic intuition is that a low-end consumer is unlikely to buy the high-end product if the high-end product is the only one she is aware of, but a high-end consumer will buy the low-end product if she is only aware of the low-end product. Therefore, when advertising is costly a greater proportion of sales will come from the low-end product. Then the firm has an incentive to increase the price of the low-end product by increasing its quality. To prevent the high-end customer from buying the low-end product when she is aware of both products, the price of the high-end product has to be lowered.

A recent paper by Lin and Narasimhan (2006) studied the interaction between product line decision and persuasive advertising. They suggested that persuasive advertising might increase consumers' willingness to pay for quality. Consequently, they showed that the prices and quality levels of both high- and low-quality products would increase when a firm adopted persuasive advertising strategy.

3.4 Cost-related issues

Researchers have also studied various impacts of cost and cost interdependence on product line pricing. Gerstner and Hess (1987) offered explanations for the empirical phenomenon of quantity discount and quantity premium observed for products in large packs. A product line with the same product sold at different pack sizes can be viewed as a special type of vertically differentiated product line if free disposal is assumed. The authors

showed that consumers' storage costs and transaction costs played significant roles in determining quantity discount versus quantity premium for products in large pack sizes. In particular, quantity premium prevails when customers differ only in their storage costs but quantity discount prevails when customers differ only in their transaction costs.

Balachander and Srinivasan (1994) examined the product line pricing by an incumbent firm that used prices to signal its cost advantage in order to deter entry. They found that credible signaling required the firm to offer higher quality and higher price of each product in the line than in the perfect-information case. The intuition is that it is prohibitively costly for a firm without cost advantage to mimic the high quality level of each product in the line. Thus, high quality credibly signals the cost advantage. In contrast to the result from the standard model (e.g. Moorthy, 1984), the quality of the lower-end product can be distorted to a higher than efficient level when quality and price are used to signal cost advantage.

Shugan and Desiraju (2001) studied the optimal adjustments of product prices in a line given the cost change of a product. Somewhat different from the standard assumptions made in the literature (e.g. Moorthy, 1984), their assumptions on demand interdependence were based on the empirical findings by Blattberg and Wisniewski (1989), who suggested that competition between quality tiers was asymmetric. That is, consumers are more likely to switch up to buy the high-quality product when it cuts price than switch down to buy the low-quality product when its price is reduced. Shugan and Desiraju (2001) found that when the cost of high-quality product declined, the prices of all products in the line should decrease. But when the cost of low-quality product declined, the prices of the high-quality product should increase while the price of the low-quality product should decrease. The driving force behind those results is that the high-quality product is mostly immune to the price cut by the low-quality product, so that preventing the H-type from switching down is not a major concern as in the standard case (e.g. Moorthy, 1984).

Desai et al. (2001) examined the pricing implications where products in a line could share common components, which reduced the production costs due to economies of scope. An interesting finding is that the firm has to increase the price of the low-end product and reduce the price of the high-end product if it lets the low-end product share a premium common component used for the high-end product. This is because the quality of the low-end product increases through sharing. This leads to a price increase for the low-quality product. The price of the high-quality product has to decrease in order to prevent the H-type from switching down.

Netessine and Taylor (2007) explored the impacts of production technology and economies of scales on product line decisions. Their model combines the standard product line model as in Moorthy (1984) with the EOQ (economic ordering quantity) production cost model, and allows product line design and production schedule to be optimized simultaneously. They found that the results from their model could be significantly different from the standard results found in Moorthy (1984). The main reason is that, compared to the standard case, a firm is likely to offer fewer products in a line in the presence of inventory costs and economies of scales. This intuition is also obvious from the numerical example discussed in Section 3.1. Given the assumptions made in that example, if the cost of producing the second unit is half the cost of producing the first unit, then only one product will be produced at $q = 2.5$ and $p = 6.25$ with the sales of two units.

4. Pricing horizontally differentiated product lines

Recall our definition of horizontal differentiation from the Introduction. It is interesting that the retail prices for products in a horizontally differentiated product line tend to be uniform. For example, supermarkets typically charge the same price for yogurt with different flavors, department stores typically charge the same price for clothes with different sizes, and video rental stores typically charge the same rental price for new DVDs. Due to the uniform pricing phenomenon, research on pricing horizontally differentiated product lines has focused on the impact of the product line length, i.e. the number of products in the line, or the overall price level of the product line. I discuss this stream of research below, followed by a discussion on the rationales behind the uniform pricing behavior.

4.1 Product line pricing and product line length

According to Lancaster (1990), there are three drivers for firms' product line length decisions: the cost consideration, the demand consideration and the strategic consideration.

The main cost consideration in determining the product line length is economies of scale (Lancaster, 1990). Because of economies of scale, an increase in the product line length leads to an increase in cost, as the demand of each product tends to be lower with more products in the line. This argument suggests that a longer product line is associated with higher price because of the increase in cost. However, if we take the product line length decision as endogenous, a high level of economies of scale would lead to a short product line because of the cost consideration. Then a short product line could imply a high price because the observed product line length resulted from high production costs. The empirical evidence on the actual relation between product line length and production costs is not conclusive. Kekre and Srinivasan (1990) examined this issue using PIMS (profit impact of marketing strategy) data and found no negative effects of broadening product line on production costs. Bayus and Putsis (1999) also investigated this issue using data from the personal computer industry. After controlling for the endogenous nature of the product line length decision, they found support for the positive relation between product proliferation and production costs.

The demand consideration also plays a major role in determining the product line length and price. On the one hand, due to the variety-seeking behavior of individual consumers (Kahn, 1995; McAlister, 1982), heterogeneity in consumer tastes and uncertainty in consumer preference, a product line with a large number of varieties is likely to be preferred by consumers (Hoch et al., 1999; Lancaster, 1990). This preference for varieties suggests a higher price for a longer product line. Evidence from both behavioral and empirical research has provided some support for this claim (Berger et al., 2007; Kahn, 1998; Kekre and Srinivasan, 1990; Kim et al., 2002).

On the other hand, a product line with a large number of varieties may increase consumers' costs of evaluating the alternatives (Shugan, 1980; Hauser and Wernerfelt, 1990) because it requires significant effort to evaluate the options provided by the product line. This consequently reduces the attractiveness of a product line with a large number of varieties. To compensate for this effect, price of the product line has to be lowered. Thus a product line with a very large assortment may actually reduce consumers' purchase probability and has to be charged at a low price. Some recent behavioral and empirical studies have provided evidence on the negative effect of product line length on consumer

preference (Boatwright and Nunes, 2001; Chernev, 2003; Dhar, 1997; Iyengar and Lepper, 2000).

Through a set of experiments, Gourville and Soman (2005) showed that product line length could have either positive or negative impacts on consumer preference depending on the assortment type of a product line. They defined two assortment types: alignable and nonalignable. An alignable assortment is one in which the alternatives vary along a single, compensatory product dimension. An example of the alignable assortment is jeans that vary in waist sizes. A nonalignable assortment is one in which the alternatives vary along multiple, noncompensatory product dimensions. For example, a product line consists of a car with sunroof but no alarm system; another one with alarm system but no sunroof can be viewed as a nonlalignable assortment. Gourville and Soman (2005) found that product line length had a positive impact on consumer preference if the assortment was alignable. In contrast, product line length can have a negative impact on consumer preference if the assortment is nonalignable because it increases both the cognitive effort and the potential regret faced by a consumer. The authors also showed that simplifying the information presentation and making the choice reversible could mitigate the negative impact of product line length on consumer preference.

Draganska and Jain (2005) examined the impact of product line length on consumer preference empirically, taking into account product line competition among firms. They developed and estimated a structural model based on utility theory and game theory. In their empirical application for the yogurt category, they found evidence that consumer utility was in an inverse-U relation with the product line length of a firm. This result reconciles the findings in the aforementioned literature that documented either the positive or the negative relation between product line length and consumer preference.

The joint impact of cost and demand factors on optimal product line length and price can be demonstrated with a simple example. Suppose that a firm sells to a unit mass of consumers who are uniformly distributed along a circle of unit length. The product line is also positioned on the circle. The location of a consumer on the circle reflects her preference. If a product is at distance x from a consumer, the consumer's reservation price for the product is $1–x$. The marginal production cost is assumed be to zero but the firm incurs a fixed cost F for adding a product to the line. Given those assumptions, if the length of the product line is n, it is optimal for the firm to position its products evenly around the circle. It can be shown that the optimal price for the product line is $p = 1 - (1/2^n)$. The market is fully covered at this price, i.e. every consumer purchases the closest product, and the total profit of the firm is $\pi = 1 - (1/2^n) - nF$. In this example, the price and profit of the product line increase with its length thanks to the demand effect (as reflected by the term $1/2^n$), but the total profit of the product line can also decrease with its length due to the cost effect (as reflected by the term nF). The optimal length of the product line is determined by the tradeoff between the demand and cost effects. It can be obtained by maximizing the total profit with regard to n.

In addition to the cost and demand considerations, the strategic consideration by firms can have a significant impact on product line length and formation. The strategic consideration can be from three aspects. First, firms' decisions on product line length and formation are influenced by their competitive behavior. On the one hand, firms facing heterogeneous consumers may want to expand their product offerings in order to gain positioning advantage. On the other hand, firms may want to restrict the length of their

product lines in order to avoid head-on competition. Theoretical models on competitive product line positioning and pricing generally admit multiple equilibria (Shaked and Sutton, 1990). Brander and Eaton (1984) showed that firms' products could either be positioned in a compartmentalized fashion, with each firm focusing on a segment of the market, or in an interlaced fashion, with competition in every fraction of the market. The price of each firm's product line is expected to be higher in the first case than in the second. The authors further showed that both cases could be Nash equilibrium if firms made product decisions simultaneously, but the first case would be at equilibrium if firms made product decisions sequentially. The model in Brander and Eaton (1984) assumed that each firm was selling a fixed number of products. This assumption was relaxed in Martinez-Giralt and Neven (1988). Their theoretical model showed that firms would shorten their product line to avoid intense price competition. Therefore a shorter product line can be associated with higher price in a competitive setting.

In an empirical study on competition between Procter and Gamble and Lever Brothers in the laundry detergent market, Kadiyali et al. (1996) found that firms seemed to behave in a coordinated way in their product line pricing behavior, with each firm positioning its strong product as the Stackelberg leader in its strategic interaction with the rival's weak product. In their empirical study on the yogurt category, Kadiyali et al. (1999) also found accommodating behavior in product line competition. They showed that a product line extension gave the firm price-setting power in the market but the prices and profits of both the extending firm and its rival increased after the product line extension.

Second, the product line length decision can be made strategically by firms selling through channels. In an interesting paper by Bergen et al. (1996), they showed both theoretically and empirically that offering a large number of branded variants could reduce competition among retailers and lead to high prices and profits for both the manufacturer and the retailers. The intuition of this result is that consumers incur high shopping costs when they compare brands across retailers that carry a large number of branded variants. As a result, fewer consumers engage in comparison-shopping across retailers as the number of branded variants increases. Consequently, the competition among retailers is softened.

Finally, product line length and formation can be used as a strategic tool for entry deterrence, as suggested by Schmalensee (1978). This strategic role of product line length implies a higher price for a longer product line as a long product line deters potential competitive entry. However, Bayus and Putsis (1999) found that the entry deterrence role of product proliferation was not supported by the data used in their empirical study.

4.2 Rationales for the uniform pricing of a product line

As mentioned at the beginning of this section, the products in a horizontally differentiated product line are typically charged with a uniform price, at least at the retail level. This is surprising because one would expect both the demand elasticity and the marginal production costs to be different for different products in a line. Some explanations have been offered in the literature for this puzzling phenomenon. On the supply side, firms may incur large menu costs (Levy et al., 1997) by setting different prices for different product variants. This discourages firms from setting non-uniform prices if the gain from price discrimination is relatively small. Draganska and Jain (2006) and McMillan (2007) found empirical support for this menu-cost-based explanation as they showed that the profit gained from non-uniform pricing was small.

Several demand-side explanations were also proposed in the literature. Kashyap (1995) and Canetti et al. (1998) suggested that many firms believe they face a kinked demand curve where marginal revenue is discontinuous at some 'price points'. If the range of prices is narrow under the potential non-uniform pricing strategy, such a range may contain only one of those price points. Then setting a uniform price at such a price point can be optimal. The fairness concern of consumers (Kahneman et al., 1986; Xia et al., 2004) can also force firms to set uniform prices. Consumers may feel that the prices are unfair if product varieties with similar perceived costs are charged with different prices.

Finally, the uniform pricing policy can result from firms' strategic interactions in competition. In the context of multi-market competition (which can be analogous to product line competition), Corts (1998) showed that firms could soften competition by committing to uniform pricing if they have identical costs but the costs of consumers vary across markets. Chen and Cui (2007) suggested that consumers' fairness concern could serve as a commitment mechanism for firms to set uniform prices. In contrast to Corts (1998), they showed that firms could be better off with uniform pricing even if there were no cost variations across product markets. This is because, besides the competition mitigation effect, uniform pricing can have an additional positive effect on firms' profits as it can expand the market under certain conditions if price elasticity varies across products.

5. Future research directions

As discussed in the previous sections, researchers from many different disciplines, such as marketing, economics, psychology and operations management, have investigated various important topics in product line pricing. While much progress has been made in the last three decades, many issues relating to product line pricing remain to be studied. In this section, I discuss some future research directions that are both important and promising in my own opinion.

First, the existing literature on product line pricing has mainly focused on the cases where prices are set on per unit base. In reality, however, the total price of a product can have both a fixed fee component and a variable price (per unit price) component. A prominent example is the price structure of different wireless phone service plans. Danaher (2002) and Iyengar et al. (2007, 2008) conducted some empirical studies in this area but theoretical study on this topic is still scarce. Future research is expected to help us to better understand the issues relating to pricing product line with a sophisticated price structure.

Second, most analytical models on product line pricing are static in nature, even though the intertemporal nature of consumer behavior such as variety-seeking and brand loyalty can be a key driver for firms' product line decisions. The empirical work by Kadiyali et al. (1999) and Sudhir (2001) discussed early in this chapter indicates that the dynamic interactions among firms can have profound impacts on product line pricing. Future analytical research on product line pricing should incorporate some demand- and/or supply-side dynamic features.

Third, behavioral research has offered important insights on consumers' reactions toward product line pricing practices (Gourville and Soman, 2005; Petroshius and Monroe, 1987; Simonson and Tversky, 1992). Future analytical and empirical research can benefit from taking into consideration the behavioral aspects of product line pricing, such as the context effect, consumer fairness concern, regret for forgone choices, etc.

Orhun (forthcoming) has taken some initiative in this direction with the attempt to incorporate the context effect into the model of pricing a vertically differentiated product line.

Fourth, as discussed in this chapter, both demand interdependence and cost interdependence among products are critical to the optimal design and pricing of product lines. This suggests that integrating the research approaches from operations and marketing can be a fruitful research direction (Eliashberg and Steinberg, 1993). As shown in Netessine and Taylor (2007), many new insights could be generated by jointly modeling the demand side and the production side of product line decisions.

Fifth, even though this chapter discussed the research on pricing the vertically differentiated product line and the horizontally differentiated product line separately, in many cases the actual product offerings in a line are differentiated both vertically and horizontally. For example, a line of automobiles can be vertically differentiated on their engine powers but also horizontally differentiated on colors and other attributes. With the exception of Shugan (1989), who showed that fewer horizontal variants are offered for high-quality product than for low-quality product, little research has been done to address the issue of pricing a product line with its products interacting both vertically and horizontally. Future research should fill this gap.

Sixth, the number of empirical studies on product line pricing has been far lower than the number of theoretical studies. This imbalance is expected to change in future as high-quality data from many industries become available to academic researchers.

Finally, technology advance and the emerging of the Internet as a marketing platform have made it cost-efficient for retailers to offer a great number of varieties in certain categories, such as music titles available from iTune, books available from Amazon.com and DVDs available from Netflix. This phenomenon of having extremely proliferated product lines was coined as the 'long tail' phenomenon by Anderson (2006). It will be interesting for future research to explore the long tail phenomenon and see whether it may lead to new product line pricing implications.

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11 The design and pricing of bundles: a review of normative guidelines and practical approaches

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Abstract

Bundling, the strategy of marketing products in particular combinations, is growing in significance given the boom in high technology and e-commerce. The seller in these instances typically has to decide which form of bundling to pursue and how to price the bundle and the individual products. We have written this chapter with two main objectives. First, we have sought to draw a set of key guidelines for bundling and pricing from a large body of 'traditional' literature rooted in stylized economic models. Here we have considered factors such as the nature of heterogeneity in consumers' reservation prices, the extent of the underlying correlation in reservation prices, the degree of complementarity or substitutability, and the nature of competition. The key conclusion is that no one form of bundling is always the best. Second, we have attempted to showcase the extant methodologies for bundle design and pricing. The studies that we have considered here have an empirical character and pertain to issues of a 'marketing' nature. In the concluding section, we suggest other avenues for expanding this work.

1. Overview

Bundling – the strategy of marketing two or more products or services as a specially priced package – is a form of nonlinear pricing (Wilson, 1993).[1] The literature identifies three alternative bundling strategies. Under the pure components (or unbundling) strategy, the seller offers the products separately (but not as a bundle);[2] under pure bundling, the seller offers the bundle alone; under mixed bundling, the seller offers the bundle as well as the individual items (see Schmalensee, 1984). The seller's decision involves choosing the particular strategy and the corresponding price(s) that maximize one's objective function. Bundling is significant in both monopolistic and competitive situations, and the guidelines often differ.

Although certain seminal papers on bundling are over four decades old (e.g. Stigler, 1963), the growth in high technology, e-commerce and competition has continually given new meaning to bundling. The rationales for bundling or unbundling (or both!) come from the firm side, demand or consumer side, and the competitor side. The bundles themselves could be of complements (e.g. TV with VCR), substitutes (e.g. a two-ticket combo to successive baseball games) or independently valued products. Indeed, there

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[1] Multipart tariff, another form of nonlinear pricing, is the focus of Chapter 16 in this volume.

[2] Although pure components and unbundling are essentially the same, Venkatesh and Chatterjee (2006, p. 22) note that unbundling represents 'the strategic uncoupling of a composite product (e.g., a news magazine) into its components'. Pure components is then the slight contrast of offering two naturally separate products in their standalone form.

could be bundles of brands (e.g. Diet Coke with NutraSweet) with more than one vested seller for a product.

We have written this chapter with two main objectives. First, we have sought to draw a set of key guidelines for bundling and pricing from a large body of 'traditional' literature rooted in stylized economic models. Second, we have attempted to showcase the work of marketing scholars. This work emphasizes practical approaches to bundle design and pricing, and includes problems of a 'marketing' nature.

The classical work on bundling by economists has predominantly been of a normative nature. Related studies have examined the role of firm-side drivers such as reduced inventory holding costs by restricting product range (e.g. Eppen et al., 1991), lower sorting and processing costs (e.g. Kenney and Klein, 1983), and greater economies of scope (e.g. Baumol et al., 1982). Price discrimination is the most widely recognized demand-side rationale for (mixed) bundling (e.g. Adams and Yellen, 1976; McAfee et al., 1989; Schmalensee, 1984). Other demand-side drivers include buyers' variety-seeking needs (e.g. McAlister, 1982), desire to reduce risk and/or search costs (e.g. Hayes, 1987), and product interrelatedness in terms of substitutability and complementarity (e.g. Lewbel, 1985). Competitor-driven considerations are most notably linked to tie-in sales (see Carbajo et al., 1990), a predatory bundling strategy in which a monopolist in one category leverages that power by bundling a more vulnerable product with it. Table 11.1 provides real-world examples for the above-mentioned rationales.

At one level, the traditional economics literature has provided the primary impetus to bundling research in marketing, and a subset of marketing articles comprises direct extensions of prior work by economists. On the other hand, and as alluded to earlier, bundling research in marketing has proved novel and complementary in the following ways:

- *New methodologies and empirics* While the bundling research in economics is characterized by stylized analytical models, research in marketing has led to an array of specific approaches to aid decision-makers in optimal bundle design and pricing. Representative approaches are conjoint analysis (Goldberg et al., 1984), balance modeling (Farquhar and Rao, 1976), mixed integer linear programming (Hanson and Martin, 1990), probabilistic modeling (Venkatesh and Mahajan, 1993), and combinatorial methods (e.g. Chung and Rao, 2003). There is a much greater emphasis on empirical work in marketing.
- *'Marketing' problems, concepts and issues* Research in marketing has brought qualitatively different problems and concepts within the purview of bundling, an effort boosted by the emergence of e-commerce. Co-branding (Venkatesh and Mahajan, 1997) or the strategy of offering a bundle of two or more brands, product integration as with copier–printer–scanner–fax machine (see Stremersch and Tellis, 2002), and consolidation or bundling of information goods (see Bakos and Brynjolfsson, 2000) are examples of what we see as 'distinctively' marketing-type contexts.

While considering the entire spectrum of bundling research, we cite only a representative subset of articles. We have oriented the chapter toward certain topics only. First, we emphasize demand- and competitor-side determinants and implications of bundling and pricing. The demand-side factors we consider are the pattern of product demand,

Table 11.1 Select firm-, demand- and competitor-side rationales for (un)bundling

	Practical example	Illustrative articles
Firm-side rationales		
Lower inventory holding costs	Dodge's decision to cut down offerings of the Caravan to a few popular 'bundles'	Eppen et al. (1991)
Lower sorting costs	De Beers selling uncut diamonds as a package and not individually	Kenney and Klein (1983)
Greater economies of scope	Microsoft integrating the development of Windows and Internet Explorer apparently to reduce costs and increase quality	Baumol et al. (1982); Gilbert and Katz (2001)
Demand-side rationales		
Price discrimination (also related to correlation of valuations across consumers)	A sports franchise offering higher-priced tickets for individual events and discounted season tickets	Ansari et al. (1996); Schmalensee (1984); Venkatesh and Mahajan (1993)
Balance within a portfolio; variety-seeking	A TV station or network selecting a subset of TV programs from a broader set of options	Bradlow and Rao (2000); Farquhar and Rao (1976); Rao et al. (1991)
Complementarity	Offering ski rentals and ski lessons as a bundle	Lewbel (1985); Telser (1975); Venkatesh and Kamakura (2003)
Competitor-side rationales		
Tie-in sales and entry deterrence	IBM bundling tabulating machines and cards	Carbajo et al. (1990); Whinston (1990)
Aggregation to reduce buyer heterogeneity	A larger aggregator of information goods outbidding a smaller competitor	Bakos and Brynjolfsson (2000)
Enabling competition through unbundling to facilitate market growth	High-end manufacturer de-linking the sales of stereo receivers and speakers	Wilson et al. (1990); Kopalle et al. (1999)

correlation in reservation prices across consumers, and the degree of complementarity or substitutability. On competition, we contrast the implications of a duopoly in all versus a subset of the product categories. On the firm side, we consider the number of product categories on sale and the level of marginal costs. Second, we draw directly on normative work in bundling to provide a series of guidelines on optimal bundling and pricing. Unless otherwise noted, we treat 'optimal' behavior as one that maximizes the seller's profits in a monopoly or represents equilibrium outcome in competitive settings. Third, we review the extant methods for bundle design and bundle pricing. Our intent here is to highlight the purpose and scope of each approach. Fourth, we refrain from technical and

analytical details as much as possible. Finally, we overlook a nascent stream of bundling research in marketing that is motivated by behavioral decision theory.

In Section 2 we discuss the normative bundling guidelines rooted in classical economic theories and axioms. In Section 3 we summarize the key approaches to bundle design and pricing. We conclude with a short chapter summary (Section 4).

2. Normative guidelines on optimal bundling and pricing

By far the largest body of work within the bundling stream is analytical and normative. Articles examining demand-side rationales begin with consumers' valuations for the individual products. The value is often assumed to be deterministic. A consumer's reservation price, an operational measure of value, is simply the maximum price the customer is willing to pay for one unit of a given product (cf. Schmalensee, 1984).[3] The reservation price construct is more nuanced when seen across products for a given consumer, or across consumers. The following two aspects of reservation prices have led to important extensions:

- *Correlation in reservation prices* As price discrimination is a key driver of mixed bundling, the heterogeneity in reservation prices across consumers is of central importance. Reservation prices across consumers for two products could be positively or negatively correlated, or be independent (i.e. uncorrelated). Positive correlation could exist when consumers differ on say their income or importance for quality. Reservation prices for the bundle are the least heterogeneous when component-level reservation prices are perfectly negatively correlated.
- *(Non-)additivity* Additivity means that a consumer's reservation price for a bundle of products is the sum of his or her reservation prices for the individual products. The additivity axiom applies for independently valued products only. For complements (e.g. ski lesson + ski rental), reservation prices are super-additive, i.e. the reservation price for the bundle is greater than the sum of the reservation prices for the individual products. For a bundle of substitutes, the reservation prices are sub-additive, i.e. the bundle reservation price is less than the sum of the product-level reservation prices. Super- or sub-additivity is more generally called non-additivity.

How the component-level reservation prices are stylized has a significant bearing on the bundling and pricing implications. We see four common characterizations and related strengths and weaknesses:

1. *Discrete distributions* (e.g. Adams and Yellen, 1976; Stigler, 1963; Stremersch and Tellis, 2002) Set typically in the two-product case, discrete distributions in bundling represent the reservation prices of two to five potential consumers or segments. The objective of related studies has been to present key conjectures or highlight shortcomings with specific strategies in an anecdotal manner. Comparative statics are irrelevant in these cases and the intent is to be illustrative rather than conclusive.

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[3] A consumer's reservation price for the second, third, or higher unit of a product is central to the stream on quantity discounts – another form of nonlinear pricing. Normative bundling articles have typically focused on a consumer's unit purchase within a category.

2. *Uniform distribution* (e.g. Matutes and Regibeau, 1992; Venkatesh and Kamakura, 2003) This is the analog of the linear demand function. For a two-product case the distribution of bundle-level reservation prices would be triangular (i.e. unimodal) or trapezoidal. This form is analytically quite tractable, can capture complementarity and substitutability, but is not convenient for modeling correlation (except perfect positive/negative correlation).
3. *Normal (i.e. Gaussian) distribution* (e.g. Bakos and Brynjolfsson, 1999; Schmalensee, 1984) The sum of multiple normal random variables is also normally distributed. Thus any number of components can be considered without making the formulation more complicated. The bivariate normal distribution has the ability to capture the underlying correlation through a single parameter, a property leveraged by Schmalensee (1984). The significant downside is that no closed-form solutions are possible for the optimal price(s), thereby requiring numerical analysis.
4. *Double exponential distribution* (e.g. Anderson and Leruth, 1992; Kopalle et al., 1999) The appeal of random utility theory and logit choice models extends to bundling. Several articles on competition in bundling are rooted in this framework and model heterogeneity through the double-exponential distribution. While complementarity or substitutability can be captured in these models, to our knowledge none of the extant articles captures correlation in reservation prices across consumers through the bivariate double-exponential distribution.

The unit variable costs (or, more generally, the marginal costs) and sub-additivity in these costs are two firm-side variables that matter. Cost sub-additivity means that the unit variable cost of the bundle is less than the sum total of those of the individual items. It most often arises from economies of scope. The number of different products making up the bundle is also a relevant variable in some settings (e.g. digital goods where the number could potentially tend to infinity).

While most normative articles on bundling assume a monopolistic setting – a supposition strengthened by the power of bundling to deter competition – the impact of competition on optimal bundling and pricing is another important research avenue.

We shall consider the above variables and state key extant propositions as guidelines.

2.1 The 'simplest' anecdotal cases

As noted earlier, these are based on discrete distributions of reservation prices. The simplest bundling problem in Stigler (1963) in the context of block booking of movies yields the following guideline (keeping aside legal aspects):

G1: *For a monopolist offering two independent products with perfectly negatively correlated reservation prices across consumers, pure bundling is optimal when marginal costs are 'low'.*[4]

Pure bundling works through reduced buyer heterogeneity in bundle reservation prices. This benefit is maximized with perfect negative correlation in reservation prices,

[4] While our guidelines sound definitive, by no means do we rule out exceptions.

Table 11.2 An illustration of the power of pure bundling

Customer	Reservation price ($) for a week's rental of		
	Gone with the Wind (GW)	Getting Gertie's Garter (GGG)	GW+GGG
Theater 1	$8000	$2000	$10 000
Theater 2	$7000	$3000	$10 000

and pure bundling extracts the entire surplus, as illustrated in Table 11.2 with a variation of Stigler's example.

In this example, assuming negligible marginal costs, the seller would have netted $18 000 under pure components by pricing GW at $7000 and GGG at $2000, leaving a surplus of $2000. However, by offering the bundle alone for $10 000, the seller nets $20 000, leaving no surplus behind. Mixed bundling collapses to pure bundling (i.e. component sales are zero). Proposition P2 in Stremersch and Tellis (2002) reinforces this point. Notice that the 'low' marginal cost condition is necessary because if, say, the marginal cost of each extra copy of the movie is $4000, offering GW alone is optimal. A related intuition is discussed below.

Adams and Yellen's (1976) seminal work focuses on both the profit and welfare implications of bundling. Through a number of anecdotal examples the authors show that no one strategy – PC, PB or MB – is always the best from profit and welfare standpoints. The following guideline is significant and could be the reason that pure bundling attracts much legal scrutiny:

G2: *Pure bundling is more prone to over- or undersupply than pure components and mixed bundling.*

In support of the guideline, Adams and Yellen point to the difficulty of adhering to the principle of 'exclusion' with pure bundling in that some individuals whose reservation prices are less than a product's marginal cost may end up buying the product. This oversupply occurs because pure bundling forces the transfer of consumer surplus from one good to another. Undersupply occurs when a consumer who would have bought a subset of the components chooses to forego the bundle as buying it would violate individual rationality.

2.2 Role of marginal costs

Digitized goods and airline seats are examples of products or services with negligible marginal costs. At the other end, electronic equipment and other real hardware have significant marginal costs in relation to consumers' willingness to pay. It would be odd if the bundling and pricing guidelines for such diverse products were the same. Indeed, while it is not uncommon to see marginal costs set to zero for analytical convenience, this section underscores that the level of marginal costs has a profound impact on the attractiveness of alternative bundling strategies.

We assume here that the reservation prices are additive and the correlation coefficient is zero. A commonly used schematic representation of consumers' reservation prices for

the two product case and their choices is shown in Figure 11.1 for the alternative bundling strategies.

The upper bounds of the reservation prices for the individual products can theoretically approach infinity. Moreover, the product and bundle prices under mixed bundling need not be the same as those under pure components and pure bundling strategies respectively. There is no implicit assumption in the diagrams on the density of the bivariate distribution.

Consider the case where unit variable costs are additive:

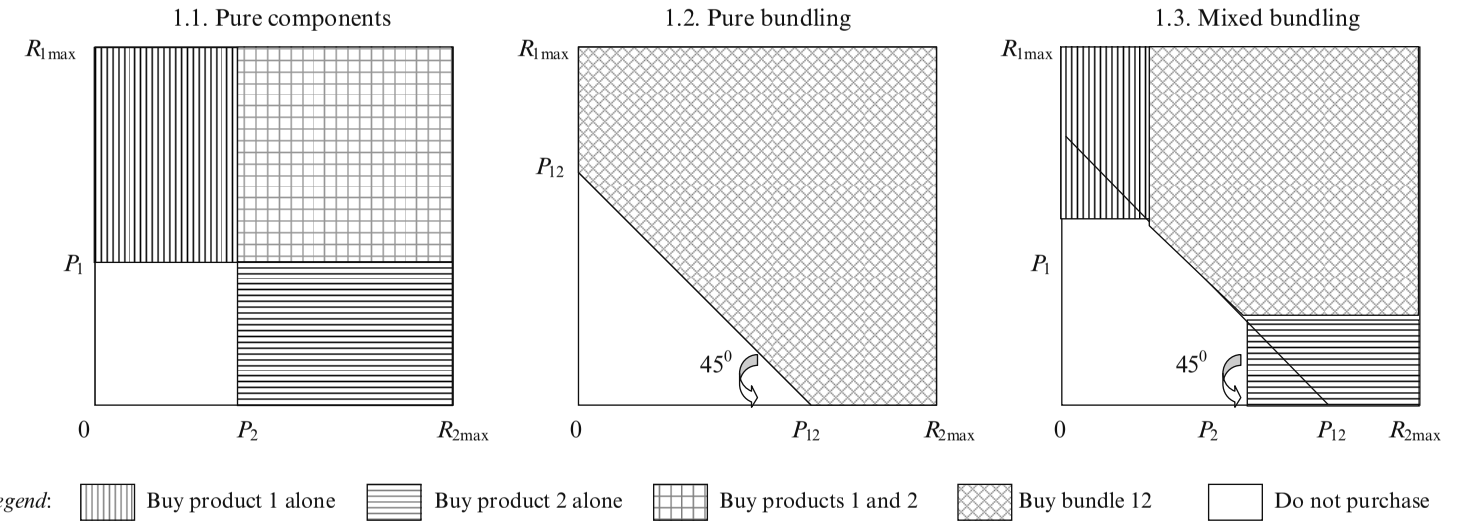
G3: *For a monopolist offering two products with symmetric Gaussian demand and costs:*
- *(a) pure bundling is more profitable than pure components when costs are low relative to mean willingness to pay; otherwise, pure components is more profitable;*
- *(b) as in G2, pure bundling makes the buyers worse off due to over- or undersupply;*
- *(c) mixed bundling is optimal.*

The result comes from Schmalensee (1984). G3(b) is a reinforcement of an earlier guideline. In a sense it drives G3(a): while the seller can effectively force the consumers to buy the bundle without incurring significant marginal costs, the same is not possible when costs are higher. The bundle price would go up significantly to cause severe undersupply; therefore the pure components strategy prevails. On G3(c) – the most significant guideline – Schmalensee (p. S227) points out how mixed bundling is a 'powerful price discrimination device in the Gaussian symmetric case'. This general strategy is able to combine the power of pure bundling to reduce buyer heterogeneity and the ability of pure components to cater to the high-end consumers of one product who care little for the other.

What if the base demand (for a product) is uniform and not Gaussian? Although the uniform and normal distributions can both have low or high standard deviation, given two supports on either side of and equidistant from the mean, the uniform distribution is thicker than the normal near these supports and thinner at the middle. Loosely speaking, the uniform distribution represents greater heterogeneity in reservation prices.

G4: *For a monopolist offering two products with uniform (i.e. linear) demand for each:*
- *(a) mixed bundling is optimal when marginal costs are low to moderate; pure components is optimal when marginal costs are high;*
- *(b) component and bundle prices are both increasing in marginal costs; however, bundle price increases are nonlinear in costs;*
- *(c) when mixed bundling is optimal, the bundle and component prices are weakly greater than under the corresponding pure strategies.*

Supporting evidence comes from Venkatesh and Kamakura (2003, p. 228). When marginal costs are low or negligible, demand-side factors dominate. With mixed bundling, the bundle is targeted at consumers who on average value both products whereas higher-priced components are sold to consumers who value one of the products highly but care little for the other product. As in Schmalensee (1984), mixed bundling can effectively



Notes:
1. Independently valued products are, by definition, neither complements nor substitutes of each other.
2. The bundle and individual product prices under mixed bundling are likely to be higher than those under the corresponding pure strategies.

Notation: $R_{1\max}$, $R_{2\max}$ = Maximum reservation price for products 1 and 2 respectively.
P_1, P_2, P_{12} = Optimal prices of product 1, product 2 and bundle 12 respectively.

Figure 11.1 Bundling with two independently valued products: schematic representation of pricing and penetration

price-discriminate. However, compared to G3, notice that the domain of optimality of mixed bundling is somewhat limited. This relates to the earlier point on the difference between uniform and Gaussian demand. Mixed bundling converges to pure components when marginal costs are high. On G4(b), the reason for the (non)linear increase in product (bundle) price is that the underlying demand function for each product is linear whereas that for the bundle has a kink – reservation prices are more concentrated in the middle. Unlike component prices that increase linearly in marginal costs, there is benefit from increasing bundle prices somewhat slowly when faced with higher costs. G4(c) is an important result on product line pricing. A wider product line – consisting of the bundle and the separate components – means that the offerings are weakly closer to consumers' ideal preferences (than under pure components or pure bundling), and the firm can charge a higher price compared to a case when it offers only a subset of these items.

While G3 and G4 are relevant when the seller has a limited portfolio of 'traditional' products with some level of marginal costs, a seller of information goods – which are numerous and practically costless – can draw on the following guideline.

G5: *For a monopolist offering a large number of products with zero marginal costs, pure bundling is optimal.*

The guideline is based on Bakos and Brynjolfsson (1999). The authors draw on the law of large numbers to point out that for a bundle made up of many goods whose valuations are distributed independently and identically, a considerable fraction of consumers has moderate valuations. This fraction approaches unity as the number of goods gets infinitely large. The assumption of zero (or negligible) marginal costs is crucial because the authors also point out that there is a marginal cost level beyond which bundling becomes less profitable.

It is easy to see that when the marginal cost of the bundle is sub-additive in those of the components, the relative attractiveness of pure bundling is likely to increase.

2.3 Role of correlation in valuations

The nature and extent of correlation in reservation prices across consumers for the product offerings significantly impacts the power of bundling as a price discrimination device.

We rely on Schmalensee (1984) for the following guideline:

G6: *For a monopolist offering two products with symmetric Gaussian demand and costs:*
- *(a) the attractiveness of pure bundling increases relative to pure components as the correlation coefficient decreases (i.e. tends to −1); however, reservation prices need not be negatively correlated for pure bundling to be more profitable;*
- *(b) the level of marginal costs in relation to the mean reservation prices of the product and bundle moderate the effectiveness of bundle sales relative to product sales;*
- *(c) as in G3(c), mixed bundling is optimal.*

The effectiveness of pure bundling comes from the reduced heterogeneity in reservation prices for the bundle. G6(a) from Schmalensee (1984) disproves the myth created by

anecdotal examples on bundling that a negative correlation in component-level reservation prices is necessary for reduced bundle-level heterogeneity. With Gaussian demand for the individual products, the benefit of heterogeneity reduction occurs so long as the correlation coefficient is less than +1. Of course, with negative correlation the heterogeneity reduction is greater, and the domain of attractiveness of pure bundling over pure components increases.

A perfectly negative correlation coefficient (of −1) means that the bundle-level reservation prices of all consumers equal the mean value. G6(b) is striking in that even this is not enough to lift pure bundling over pure components. Echoing the point in G1, pure bundling will yield a negative contribution when the marginal cost of the bundle is greater than the mean reservation price. Pure components would prevail.

G6(c) is the succinct generalization from Schmalensee, noted previously in G3. Of course, the share of bundle sales relative to individual product sales depends on the degree of correlation and the level of marginal costs in relation to willingness to pay. When the correlation coefficient approaches +1 (or −1), mixed bundling is expected to converge to pure components (or pure bundling). Of course, the caveat in part (b) will apply.

2.4 Role of complementarity or substitutability

By definition, reservation prices are super- (or sub-) additive for complements (or substitutes). Guiltinan (1987) proposes at least three possible sources of complementarity: (i) search economies, as for oil change performed at the same gas station and at the same time as a filter change; (ii) enhanced customer satisfaction, as for a ski rental accompanied by a lessons package; and (iii) improved total image, as for lawn care services offered with shrub care services (also see Oxenfeldt, 1966). Two products are seen as substitutes when their benefits overlap at least in part (e.g. international business news in the *Financial Times* and *The Wall Street Journal*) or when they compete for similar resources such as a consumer's time. While it may seem at first glance that complements should be bundled and substitutes offered separately, the truth is more nuanced. The normative guidelines that follow are from Venkatesh and Kamakura (2003).

We assume for this subsection that reservation prices across consumers for the two products are uncorrelated. The unit variable costs are additive:

G7: *For a monopolist offering two complements with uniform (i.e. linear) demand for each:*

(a) pure bundling is more profitable than pure components only when (i) marginal costs are low or (ii) the products are strong complements;

(b) when all three strategies are available, (i) mixed bundling is optimal for weak complements when the marginal costs are low to moderate; (ii) pure components is optimal for weak complements when marginal costs are high; (iii) pure bundling is optimal for strong complements.

G7(a) underscores that the pure components strategy actually prevails over pure bundling for a wide range of complements, falling short only for strong complements or when the marginal costs are low relative to the market's mean willingness to pay. In the latter case (with low marginal costs), the seller has more flexibility to offer significant discounts on the bundle and induce joint purchase. It is exactly the upward pressure on prices due

to higher marginal costs that makes pure bundling less profitable than pure components for low to moderate complements.

The significance of G7(b) is that while the power of mixed bundling extends to moderate complements also when marginal costs are low, it is not a dominating strategy. For strong complements, bundling is so attractive that mixed bundling actually converges to pure bundling. On the other hand, when marginal costs are higher, the lowest possible bundle price is so high that mixed bundling converges to the pure components strategy; offering discounts via the bundle to consumers in the 'middle' (i.e. with moderate reservation prices for both products) is suboptimal.

The following guideline applies for substitutes.

G8: *For a monopolist offering two substitutes with uniform (i.e. linear) demand for each:*
- *(a) pure components is optimal for strong substitutes and mixed bundling for weak substitutes;*
- *(b) when marginal costs are higher, the domain of optimality of pure components relative to mixed bundling is enlarged;*
- *(c) pure bundling is suboptimal.*

Part (c) is intuitive yet significant in that enticing consumers with discounts for the bundle under the pure bundling strategy is suboptimal for substitutes. A better alternative is to focus on consumers who care for one product or the other, and let those who have high prices for both products form their own implicit bundles at higher prices. Indeed, discounted bundles are of such limited appeal that mixed bundling converges to pure components for all but the weak substitutes, a trend amplified under higher marginal costs.

The underlying mechanism for the above guidelines is evident from the pricing patterns discussed below.

G9: *For a monopolist offering two complements or substitutes with uniform (i.e. linear) demand for each:*
- *(a) under pure components, optimal prices of complements and most substitutes are weakly higher than those of independently valued products;*
- *(b) under pure bundling, the optimal bundle price is lower for substitutes and higher for complements than that for independently valued goods;*
- *(c) under mixed bundling, the bundle and component prices are weakly greater than under the corresponding pure strategies.*

The obvious part of the above guideline is that prices under both pure components and pure bundling are increasing in the degree of complementarity; after all, stronger complements are more valuable to consumers and higher prices help extract this higher value. The interesting aspect is that the optimal prices under pure components are higher for substitutes than for independently valued products. Relating back to G8, it actually helps not to encourage joint purchase of a suboptimal combination. Because pure bundling lacks this flexibility (i.e. it can only induce joint purchase), it is dominated. To be sure, mixed bundling is still the best for mild substitutes when the marginal costs are low to moderate.

2.5 Role of competition

Besides price discrimination, the rationale most often attributed to bundling is its ability to deter a new entrant or dislodge an incumbent. Kodak's decision to bundle film with processing, IBM's tie-in of tabulating machines and related cards, and the more recent example of Microsoft's integration of Internet Explorer with its Windows/Vista operating systems are prominent examples. We review a set of proposed guidelines on optimal bundling and pricing.

The simplest example of competition is when firm 1 enjoys a monopoly in product category A but competes with firm 2 in a category B. The available products are A_1, B_1 and B_2. If firm 1 follows pure bundling, a consumer who strongly prefers A_1 and B_2 is forced to buy the bundle A_1B_1 and the product B_2, an obvious case of oversupply. When the two product categories are independent of each other, some consumers may buy B_2 alone. However, if the product categories are strict complements – such as TV and DVD player – the power of the tie-in becomes evident. While the Robinson Patman Act prohibits the use of pure bundling in B2B settings, the same is not true for B2C contexts, especially when firm 1 can justify pure bundling as a prerequisite for ensuring overall quality (as Kodak was once able to argue). We first look at the simplest case with independent demand. All articles cited in this subsection assume uncorrelated valuations across consumers for the products in question.

G10: *Given two product categories with independent uniform (i.e. linear) demand, when a monopolist in the first product category faces a competitor in the second category:*
- *(a) given a Bertrand game in the second category, the monopolist in the first category prefers pure bundling when the marginal cost of the monopoly good is 'large enough' compared to that of the other;*
- *(b) the bundle price of the monopolist in the first category is increasing more rapidly in the marginal cost of the good in the second category;*
- *(c) the competitor's single product price (for the second product) is higher when the monopolist in the first category prefers pure bundling over pure components.*

The guideline comes from Carbajo et al. (1990). The authors point out that in equilibrium, the monopolist pursuing pure bundling is able to clear consumers with the highest reservation prices. Of the remaining consumers, the competitor clears those with the higher reservation prices and excludes those with the lowest reservation prices for the second product. Had the monopolist pursued pure components, the equilibrium prices for the competing products in the second category would have been driven down to marginal costs. Thus the tie-in actually makes both manufacturers better off while aggregate welfare typically suffers.

A more general form of competition is when there is a duopoly in both product categories (e.g. Matutes and Regibeau, 1992; henceforth MR). Consumers could potentially buy two products from the same firm (that MR label 'pure systems') or mix between the two firms (i.e. form 'hybrid systems' as per MR). The following guideline applies:

G11: *In a two-product duopoly with linear demand for each product:*
- *(a) pure components dominates pure bundling when the firms offer compatible products; otherwise, pure bundling prevails;*

(b) for compatible products, the choice between pure components and mixed bundling depends on the consumers' valuation of their 'ideal bundle'; when consumers are very particular about their 'ideal bundle', pure components is better.

The guideline comes from MR. Incompatible offerings from the two firms would mean that the consumer has to make the decision at the system (i.e. bundle) level. Pure bundling prevails. However, with compatible offerings from the two firms, the customer's decision is driven by his or her preference intensity for an ideal combination – the pair that the customer finds the most complementary. If the preference intensity for this combination is very high, the firms are better off with pure components, i.e. giving the customer the most flexibility to put together a hybrid system (i.e. a mix of products from the two manufacturers) or a pure system as desired. There is no need to offer a discounted bundle through mixed bundling because when the complementarity from a pure system is strong enough, the customer is self-motivated to buy both products from the same firm.

Anderson and Leruth (1992) look at a variation of the above problem in which the products from different firms are assumed to be compatible but the heterogeneity in valuations of each product is captured by the double-exponential distribution. Broadly echoing MR, Anderson and Leruth find that if firms can commit to a pricing strategy before setting prices, pure components will be the equilibrium strategy for both firms; otherwise, each firm will pursue mixed bundling.

Building on the above, Kopalle et al. (1999) consider the possibility of market expansion (i.e. an unsaturated market). The key conclusion is that the equilibrium strategies of the firms shift from mixed bundling to pure components when there is limited opportunity for market expansion. The rationale is that when the market is less saturated, each firm can entice more customers by offering a wider product line (i.e. offer both the bundle and the individual products). With saturation, the incentive to entice customers with the discounted bundle is removed.

Given a large number of products in the context of the information economy, we have:

G12: *In a duopoly between bundlers of goods with zero marginal costs and i.i.d. reservation prices:*

(a) the firm offering the larger bundle will find it more profitable to add an outside good;

(b) by extension, a firm bundling information goods will be able to deter or dislodge a firm that offers a single information good.

The results are from Bakos and Brynjolfsson (2000), and build on their 1999 study. They invoke the law of large numbers to demonstrate that a firm with a larger bundle of 'costless' information goods is better able to reduce heterogeneity in consumers' valuations. Therefore, in a competition between two firms offering bundles of n_1 versus n_2 goods ($n_1 > n_2$), firm 1 would be better able to extract the consumers' surplus and hence would find it more profitable. The greater power of the larger bundler lets it deter a prospective entrant or dislodge an incumbent firm.

Table 11.3 contains a summary of our above guidelines, the underlying drivers for each guideline, and the articles that provide the supporting evidence.

We see additional linkages such as the following among the above guidelines. Higher

Table 11.3 A summary of normative guidelines on optimal bundling and pricing

Underlying driver(s)	Guidelines	Supporting evidence
Discrete demand (anecdotal cases)	G1: For a monopolist offering two independent products with perfectly negatively correlated reservation prices across consumers, pure bundling is optimal when marginal costs are 'low'.	Stigler (1963) Stremersch and Tellis (2002)
	G2: Pure bundling is more prone to over- or undersupply than pure components and mixed bundling.	Adams and Yellen (1976)
Marginal costs and number of product categories	G3: For a monopolist offering two products with symmetric Gaussian demand and costs: (a) pure bundling is more profitable than pure components when costs are low relative to mean willingness to pay; otherwise, pure components is more profitable; (b) as in G2, pure bundling makes the buyers worse off due to over- or undersupply; (c) mixed bundling is optimal.	Schmalensee (1984)
	G4: For a monopolist offering two products with uniform (i.e. linear) demand for each: (a) mixed bundling is optimal when marginal costs are low to moderate; pure components is optimal when marginal costs are high; (b) component and bundle prices are both increasing in marginal costs; however, bundle price increases are nonlinear in costs; (c) when mixed bundling is optimal, the bundle and component prices are weakly greater than under the corresponding pure strategies.	Venkatesh and Kamakura (2003)
	G5: For a monopolist offering a large number of products with zero marginal costs, pure bundling is optimal.	Bakos and Brynjolfsson (1999)
Correlated valuations	G6: For a monopolist offering two products with symmetric Gaussian demand and costs: (a) the attractiveness of pure bundling increases relative to pure components as the correlation coefficient decreases (i.e. tends to –1); however, reservation prices need not be negatively correlated for pure bundling to be more profitable;	Schmalensee (1984)

Table 11.3 (continued)

Underlying driver(s)	Guidelines	Supporting evidence
	(b) the level of marginal costs in relation to the mean reservation prices of the product and bundle moderate the effectiveness of bundle sales relative to product sales; (c) as in G3(c), mixed bundling is optimal.	
Complements and substitutes	G7: For a monopolist offering two complements with uniform (i.e. linear) demand for each: (a) pure bundling is more profitable than pure components only when (i) marginal costs are low or (ii) the products are strong complements; (b) when all three strategies are available, (i) mixed bundling is optimal for weak complements when the marginal costs are low to moderate; (ii) pure components is optimal for weak complements when marginal costs are high; (iii) pure bundling is optimal for strong complements.	Venkatesh and Kamakura (2003)
	G8: For a monopolist offering two substitutes with uniform (i.e. linear) demand for each: (a) pure components is optimal for strong substitutes and mixed bundling for weak substitutes; (b) when marginal costs are higher, the domain of optimality of pure components relative to mixed bundling is enlarged; (c) pure bundling is suboptimal.	Venkatesh and Kamakura (2003)
	G9: For a monopolist offering two complements or substitutes with uniform (i.e. linear) demand for each: (a) under pure components, optimal prices of complements and most substitutes are weakly higher than those of independently valued products; (b) under pure bundling, the optimal bundle price is the lower for substitutes and higher for complements than that for independently valued goods; (c) under mixed bundling, the bundle and component prices are weakly greater than under the corresponding pure strategies.	Venkatesh and Kamakura (2003)

Competition	G10: Given two product categories with independent uniform (i.e. linear) demand, when a monopolist in the first product category faces a competitor in the second category: (a) given a Bertrand game in the second category, the monopolist in the first category prefers pure bundling when the marginal cost of the monopoly product is 'large enough' compared to that of the other; (b) the bundle price of the monopolist in the first category is increasing more rapidly in the marginal cost of the product in the second category; (c) the competitor's single product price (for the second product) is higher when the monopolist in the first category prefers pure bundling over pure components.	Carbajo et al. (1990)
	G11: In a two-product duopoly with linear demand for each product: (a) pure components dominates pure bundling when the firms offer compatible products; otherwise, pure bundling prevails; (b) for compatible products, the choice between pure components and mixed bundling depends on the consumers' valuation of their 'ideal bundle'; when consumers are very particular about their 'ideal bundle', pure components is better.	Matutes and Regibeau (1992)
	G12: In a duopoly between bundlers of goods with zero marginal costs and i.i.d. reservation prices: (a) the firm offering the larger bundle will find it more profitable to add an outside good; (b) by extension, a firm bundling information goods will be able to deter or dislodge a firm that offers a single information good.	Bakos and Brynjolfsson (2000)

marginal costs appear to increase the significance of the individual components *vis-à-vis* the bundle (and vice versa). This explains why guideline G4(a) on the superiority of pure components over pure bundling for independently valued products with high marginal costs extends even to moderate complements (G7(a)). While the power of pure bundling comes from reduced heterogeneity in the reservation prices for the bundle, guidelines G1 and G6(a) (from Schmalensee, 1984 and Stigler, 1963) together suggest how a negative correlation augments this advantage, a point also made by Salinger (1995, p. 98). The presence of a large number of low-marginal-cost products also aids in reducing buyer heterogeneity for the bundle. Guideline G12 (from Bakos and Brynjolfsson, 2000) points out that an aggregator of a larger number of low-cost products can wield greater power through pure bundling compared to a smaller rival.

3. Approaches for bundle design and pricing

At one level, bundling is a product line decision. Therefore product line design and product line pricing approaches have some relevance to bundling. On the other hand, bundling is different from a product line problem because the latter involves a set of 'similar' or substitute products, such as the line of Toyota cars. The products that make up a bundle could have a broader array of interrelationships such as substitutability, independence or complementarity, and positively or negatively correlated reservation prices. Farquhar and Rao (1976) point to the need for 'balance' among products that make up a bundle. McAlister (1982) links consumers' evaluations of bundles to their variety-seeking needs and proposes the concept of attribute satiation as a driver of portfolio choice. While product line approaches are complicated, approaches to bundling are arguably even more challenging (and cumbersome).

Methodological approaches to bundling come in one of two broad types. Design-oriented approaches (e.g. Bradlow and Rao, 2000; Chung and Rao, 2003; Farquhar and Rao, 1976; Goldberg et al., 1984) help identify which among a feasible set of 'products' should go into the bundle (e.g. the composition of a professional basketball team) or what the levels of specific attributes should be (e.g. designing the make-up of a hotel in terms of the type of room, lounge etc.). Pricing-oriented approaches (e.g. Ansari et al., 1996; Hanson and Martin, 1990; Venkatesh and Mahajan, 1993) typically assume a product portfolio and propose the prices at which the individual items and/or bundles should be offered.

There is of course a design element to pricing-oriented approaches in the sense that if the proposed price of a product is 'too high', it essentially means withdrawing the product from the final set of offerings. However, the design focus is lacking in the sense that if a new component (not in the original portfolio) is added, the model has to be re-estimated (see Chung and Rao, 2003, p. 115). Likewise, while a typical design-oriented approach, say of Chung and Rao, answers certain pricing questions, its pricing focus is typically limited to a subset of strategies – pure bundling in Chung and Rao. By contrast, a component level approach, say Hanson and Martin (1990), provides optimal prices for all three alternative bundling strategies. Thus the distinction between a design versus a pricing emphasis in the extant approaches broadly holds.

Based on Chung and Rao's classification, design-oriented approaches are more likely to be attribute-level approaches (e.g. Bradlow and Rao, 2000) that model the complementarity among product attributes to capture bundle-level valuation. Pricing-oriented approaches are typically component level methodologies (e.g. Hanson and Martin, 1990);

that is, they treat 'components of a bundle as the ultimate unit of analysis in describing the utility of the bundle' (Chung and Rao, 2003, p. 115).

A key input for most pricing-oriented approaches is the consumers' reservation prices for the individual products and the bundle. Indeed, significant bias and/or measurement error in eliciting reservation prices could severely affect the appropriateness of the proposed optimal prices. Several recent studies such as Jedidi et al. (2003), Jedidi and Zhang (2002), Wang et al. (2007), Wertenbroch and Skiera (2002), and Wuebker and Mahajan (1999) propose interesting and effective ways of measuring reservation prices. The reader is referred to Chapter 2 in this book by Jedidi and Jagpal on estimating or eliciting reservation prices.

We now discuss representative design- and pricing-oriented approaches to bundling.

3.1 Design-oriented approaches to bundling

The diversity in the bundles to be designed has led to several types of design-oriented approaches. Our review focuses on the following routes summarized in Table 11.4:

- Hybrid categorical conjoint analysis (Goldberg et al., 1984)
- Balance model (Farquhar and Rao, 1976) and its later adaptations (e.g. Bradlow and Rao, 2000; Chung and Rao, 2003) (Rao and colleagues, hereafter)
- Co-branding approach (Venkatesh and Mahajan, 1997).

Table 11.4 contains the inputs to and outputs from each approach, and its key strengths and weaknesses. We devote this subsection to a discussion of the underpinnings of each approach.

(Hybrid categorical) conjoint approach Conjoint analysis is a well-established methodology in marketing for evaluating consumers' preferences for multi-attribute items and, in turn, as a product development tool. Goldberg et al.'s (1984, GGW) hybrid categorical conjoint approach is an improvement over basic conjoint in that it can deal with correlated attributes (e.g. hotel room price is typically correlated with room size) and provide bundle combinations and price premiums (i.e. express 'the price premiums for each amenity and also for competing bundles of amenities', GGW, p. S112). The GGW approach is preferable especially when a large number of attributes (40+ in their hotel context) and attribute levels (100+) are involved.

The 'hybrid' aspect of GGW's approach comes from simplifying the data collection task while still accounting for certain individual differences. Each respondent evaluates 'the levels of each attribute (one at a time) on some type of desirability scale' (Wind et al., 1989). The respondent is then exposed to a subset of the universal set of profiles so that only the main effects and select interactions are estimated. The 'categorical' element connotes that unlike with 'ordinal' approaches such as LINMAP, the dependent variable capturing preference need not be ordered. GGW's approach is implemented with 'dummy variable canonical correlation'.

The balance modeling approach The original balance model and its variants by Rao and colleagues have two core premises: one, that the selection of products that go into a bundle should consider the interactions among the attributes that define the

Table 11.4 Comparison of alternative approaches to optimal bundle design

Framework and representative articles	Inputs (what the approach needs)	Output (what the approach provides)	Strengths	Limitations
Conjoint analysis • Goldberg et al. (1984) (GGW)	• Respondents' choices at an attribute level, preference importance of attributes, and the likelihood of choosing specific bundles: collected in three phases	• The bundle of amenities and add-ons to be offered, and associated prices (or premiums) • Attribute importance and part-worths	• Extends conjoint analysis to the case of correlated attributes (as in bundling contexts) • A large number of attributes and levels can be handled with categorical hybrid conjoint	• As with traditional conjoint studies, cost of the offerings is not factored in; profit implications of bundle design are unavailable
Balance model • Bradlow and Rao (2000) • Farquhar and Rao (1976)	• Respondents' assessments on which product(s) from a feasible set balances a given (pair of) product(s); pairwise comparisons	• Identification of the best balanced product combinations • Classification of attributes as balancing, non-balancing, or non-essential	• 'Balance', a fundamental driver of consumers' bundle-choice decisions, is captured • Models bundle-level decision as a multi-attribute problem, helps clarify sources of interdependencies	• Pricing is not the focus; determining the makeup of the bundle is • Number of products making up a bundle is exogenous (to keep data collection manageable)
Comparability-based balance model • Chung and Rao (2003)	• Consumers' self-explicated bundle choices in a series of choice tasks, and reservation prices for their 'best' bundle • Consumers' ratings of the products on importance and comparability	• Identification of market segments for candidate bundles • Estimation of consumers' bundle-level reservation prices • Optimal bundle prices	• Integrates the key elements of conjoint analysis and balance model • Considering assortments across product categories improves upon prior balance modeling articles	• Mixed bundling strategy is not considered • Classification of attributes based on their balancing character could overlook perceived differences across consumers

Co-branding approach • Venkatesh and Mahajan (1997)	• Consumers' reservation prices for alternative co-branded offerings, and allocation of preference intensities between brands within each offering	• Best alliance partners and product combinations • Optimal prices, profits and (asymmetric) benefits for the respective partners	• By modeling the enrichment or suppression among brands, clarifies the asymmetric returns to alliance partners • General parametric distribution used to capture heterogeneity in valuations and (dis-synergies)	• Model is implemented for a product with two component brands only

products; and two, the bundle so chosen should be one that provides the best balance of features.

Balance represents the 'general harmony [among] the parts of anything, springing from the observance of just proportion and relation' (*Oxford English Dictionary*). Balance, as Rao and colleagues note, could come from homogeneity on some attributes and heterogeneity on others. Setting aside 'non-essential' attributes, the balance approach seeks to classify the remaining essential attributes as balancing and non-balancing. Balancing attributes can be equibalancing or counterbalancing; consumers seek heterogeneity on counterbalancing attributes (e.g. color, as in the assortment of shirts that consumers might like to own) and homogeneity on equibalancing attributes. Non-balancing attributes are those on which consumers wish to maximize (or minimize) aggregate scores as with quality (or costs).

The seminal paper in the stream by Farquhar and Rao (1976) – implemented in the context of scheduling TV programs – takes consumers' self-explicated measures on a series of 'balance'-related questions (see Table 11.3) and uses linear programming to classify attributes and select the most balanced bundle(s) from the possible alternatives.

The extension proposed by Bradlow and Rao (2000) relies on a hierarchical Bayesian model to implement the balance framework at the level of individual consumers as in their magazine or video purchasing behavior. The approach can help managers identify the best prospects for pre-existing product assortments as well as identify the specific bundle that would be appealing to the highest number of customers.

While the above two articles deal with bundle selection in 'homogeneous' categories (e.g. among television programs), the recent article by Chung and Rao (2003) proposes how a bundle of items from across categories could be identified. The approach tackles the possible non-comparability among attributes – a problematic issue for the traditional balance model. The proposed approach gets consumers' input to trifurcate attributes as comparable, partially comparable and non-comparable. Comparable attributes essentially become system-level attributes with possible interaction. Also, while computing sums and dispersion scores, the approach weights the components differently depending on their importance. The authors apply their approach to the context of personal computer systems.

Co-branding approach Bundles of co-branded products, such as 'Lenovo PCs with Intel Inside', represent an emerging class of product combinations. Such bundles arise out of firms' motivation to emphasize their core competencies and forge alliances with synergistic partners. Unlike the other examples discussed in this subsection, co-branded bundles represent a coming together of two or more firms. The Venkatesh and Mahajan (1997, VM) approach is suitable for partner selection and pricing in co-branded bundles.

VM note that it would not suffice to consider only the aggregate payoffs from the co-branded bundles. Rather, the payoffs attributable to either partner should be distinguished because the benefit or cost from forming the brand alliance could be asymmetric depending on the prior reputation of the two brands and the nature of spillover. The approach defines a positive spillover to a brand as 'enrichment' and a negative spillover as 'suppression'. The heterogeneity in consumers' valuations for the base bundles (those between a branded offering and a generic) and in the perceived spillover effects are used to identify the best partners, the asymmetric benefits to the partners, the optimal prices and

premiums for the baseline and co-branded bundles, and the corresponding payoffs. These decisions and outcomes are clarified in the context of the personal computer category and involving Compaq and Intel.

3.2 Approaches to bundle pricing

We devote this subsection to a discussion of the following three significant and diverse approaches to bundle pricing. These are summarized in Table 11.5:

- Mixed integer linear programming (Hanson and Martin, 1990)
- Probabilistic approach (Ansari et al., 1996; Venkatesh and Mahajan, 1993)
- Choice experiment-based hierarchical Bayesian approach (Jedidi et al., 2003)

While each approach's inputs and outputs, and the key strengths and weaknesses, are shown in Table 11.5, our discussion below focuses on the underpinnings and the key empirical findings.

Mixed integer linear programming approach Bundle pricing is a particularly complicated problem when the number of products is three or higher. With n distinct products, the number of possible offerings – consisting of all standalone products and bundles – is 2^{n-1}. Hanson and Martin's (1990) mixed integer linear programming approach is appropriate for a monopolist seeking to set the optimal prices for such a large-scale problem, given the right inputs.

The approach requires consumers' (or their segments') reservation prices and the seller's unit variable costs for all the possible offerings. In the limit, a segment could be made up of a single consumer. Making a reasonable set of assumptions, the article first establishes that a profit-maximizing vector of prices exists provided that each customer will purchase exactly one product or bundle or neither. A disjunctive approach that reduces computational times is used to determine the optimal solution. The approach is implemented with survey data on consumers' preferences for home services such as apartment cleaning.

Probabilistic approach While bundling articles typically assume that the key constraint at the consumer level is the willingness to pay, the probabilistic approach of Venkatesh and Mahajan (1993) and Ansari et al. (1996) is relevant for products such as entertainment or sports events for which other constraints such as available time are also significant in consumers' decision-making. While Venkatesh and Mahajan's approach is aimed at a profit-maximizing monopolist, Ansari et al. extend it to non-profits such as certain symphonies and museums. The components in these instances are the individual events or games, and the bundle is the package of such events. The single and season ticket prices are optimized.

The two studies, based on the same dataset and similar consumer choice processes, are probabilistic in the sense that they recognize potential consumers' uncertainty with finding the time for temporally dispersed events, even when they may have strong tastes for the events in question. The modeling approach translates the dispersion in consumers' reservation prices for the individual events and the heterogeneity in their time-related uncertainty to the bundle level, and provides the optimal single and season ticket prices.

Table 11.5 Comparison of alternative approaches to optimal bundle pricing

Framework and representative articles	Inputs (what the approach needs)	Output (what the approach provides)	Strengths	Limitations
Mixed integer linear programming framework • Hanson and Martin (1990)	• Consumers' reservation prices for components and bundles • Marginal costs of components and bundles	• Optimal prices of the bundle and components • Consumers' choices and surpluses	• Superior to alternatives when a large number of components and bundles is involved • Programming tool developed by authors has interactive, decision support capability	• Focus is on setting actual prices, not on providing strategic insights • Framework is not at the attribute level and hence sensitivity of results to product additions is hard to assess
Probabilistic framework • Ansari et al. (1996) • Venkatesh and Mahajan (1993)	• Distributions of consumers' resources and preferences (e.g. heterogeneity in available time and willingness to pay) • Fixed and variable costs of the bundle/components	• Optimal prices of the bundle and/or components under pure components, pure bundling and mixed bundling • Associated profits and, hence, the optimal bundling strategy	• Integrates consumers' preference intensities (e.g. reservation prices) and constraining resources (e.g. available time) • Suited for time-variant consumption (e.g. concerts) • For-profit and non-profit contexts compared (Ansari et al.)	• Makeup of the bundle is exogenous (i.e. components that go into the bundle are predetermined) • Underlying heterogeneity on any dimension is assumed to be unimodal
Choice experiment/ hierarchical Bayesian framework • Jedidi et al. (2003)	• Consumers' reservation prices inferred through choice experiment • Fixed and variable costs of the bundle/components	• Joint distribution of reservation prices for the individual products and bundle; approach accommodates non-additivity and correlated valuations • Optimal prices, profits and the optimal bundling strategy	• Model is rooted in utility theory and allows for interrelationships among product offerings • No-purchase option captures price expectations and reference effects	• Makeup of the bundle is exogenous, as above • Assuming normal (Gaussian) heterogeneity in component-level valuations is moot for a practical methodology

In the empirical context of a series of entertainment events, Venkatesh and Mahajan find that while mixed bundling is more profitable, the single and season ticket prices have to be optimized simultaneously. That is, starting with the optimal price from pure bundling (say) and sequentially determining the component prices is likely to be suboptimal. Also, ignoring the heterogeneity in available time is likely to bias the prices significantly upward. Ansari et al. find that a non-profit is likely to offer more events and set lower prices. As increasing total attendance is more important for non-profits, pure bundling becomes more attractive than pure components.

Choice experiment-based hierarchical Bayesian approach The above two types of approaches assume that consumers' reservation prices are available, through the use of other approaches. Jedidi et al.'s (2003) choice experiment-based hierarchical Bayesian approach is apt when the seller wishes to arrive at the multivariate distribution of reservation prices for the bundle(s) and the component products, and then apply a built-in algorithmic procedure to arrive at product line prices.

The estimation of the multivariate reservation prices consists of two steps. A (hybrid) choice-based experiment makes up the first step to infer respondents' reservation prices. This part includes a no-purchase option which helps capture competitive and reference price effects, and obtain 'dollarmetric reservation prices' (Jedidi et al., 2003, p. 111). With the choice information and the corresponding price points from the first step, and with the assumption that the true distribution of reservation prices for the offerings is multivariate normal, a hierarchical Bayesian framework is used to estimate the parameters of the joint posterior distribution. Any non-additivity in bundle-level valuations is captured under this approach. The optimization algorithm to obtain the optimal prices of the product line is routine, and requires as input the marginal costs of the various offerings.

The above study by Jedidi et al. yields the following empirical results: charging high prices for the bundle(s) and the individual products is profit maximizing only when there is considerable heterogeneity in the valuations of these offerings. Otherwise, specific products/bundle(s) have to be priced low.

4. Conclusion

Consumers often purchase baskets of products from across product categories. Even when they plan to buy integrated products such as a car, they evaluate its components and how these interact. It is this issue of interrelationships among products that lends meaning and power to the strategy of bundling. Of course, the seller's own desire to reduce costs, increase efficiencies and challenge competition gives added meaning to bundling.

Our objective in this chapter has been to review and synthesize the extant literature on the design and pricing of product bundles. We have looked at the normative guidelines for bundling and pricing as well as the empirical approaches to actually design or price product bundles. Our conclusion from a normative angle is that mixed bundling does not always trump pure bundling and pure components. Indeed, depending on factors such as marginal costs, correlation in reservation prices, complementarity or substitutability, and competition, it may be appealing to the seller to pursue pure components or pure bundling. On the practical approaches, the seller has to be clear about the issues s/he is facing because different approaches apply depending on whether the focus is on design or pricing. Other deciding factors are the number of products in the portfolio, whether

these products are predetermined or have to be identified, type of data that are available or can be collected, and so on.

Space constraints have forced us to leave out several other exciting domains of bundling research. Among them are behavioral approaches to bundling that draw on behavioral decision theory and experimental evidence to argue that the assumptions of classical economics may not always hold. For example, Soman and Gourville (2001) show that for bundles of temporally dispersed events (e.g. a four-day ski pass), consumers' likelihood of attending later events (e.g. skiing on the fourth day) is lower than that for earlier events. The authors draw on the sunk cost literature to propose 'transaction decoupling' as the underlying theoretical rationale. Soman and Gourville's findings point to a research opportunity for modelers to propose an approach for overselling and pricing later events in a series. Separately, on the topic of price framing, Yadav and Monroe (1993) find that consumers separate the savings from a bundle into two parts – savings on the individual items if purchased separately, and the additional savings from buying the bundle. An implication is that even when pure bundling is the optimal strategy, a seller should consider offering the individual components as decoys that make the bundle more attractive than what rational behavior might suggest. Analytical research would benefit by recognizing these perspectives.

While we have drawn on some bundling articles motivated by e-commerce, there are several other relevant contributions to bundling (e.g. Rusmevichientong et al., 2006; Venkatesh and Chatterjee, 2006). Indeed, real-world developments in e-commerce and technology offer exciting opportunities for future work on bundling. We urge a closer look at these research avenues.

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12 Pricing of national brands versus store brands: market power components, findings and research opportunities

*Koen Pauwels and Shuba Srinivasan**

Abstract
Among the most important activities for supermarket retailers is the creation and marketing of store brands, also known as private label brands. Given the increasing quality-equivalence between national brands and store brands, they have become direct competitors, and pricing decisions should take this into account. In most cases, national brands still possess some degree of pricing and market power over store brands. In this chapter, we define three components of market power for national brands versus store brands: (1) price premium; (2) volume premium; and (3) margin premium. Our chapter proceeds along the following lines. First, we delineate the factors that are the most important drivers of the three components of premium. Second, we discuss managerial implications about key success factors in the pricing of national brands and store brands. A key contribution of this chapter is that we incorporate emerging insights from the marketing literature on the pricing and market power of national brands versus store brands. Finally, we conclude by offering important future research directions.

1. Introduction

1.1 Importance of store brands

One of the most important activities for supermarket retailers is the creation and marketing of store brands, also known as own labels, distributor-owned brands or private labels. Although store brands have been around for about a century, despite some exceptions (such as Marks & Spencer's St Michael brand), store brands were seen as poor cousins to the manufacturer brands, with a small market share that was considered unlikely to become significant. Recently, store brands have enjoyed tremendous success at the expense of national brands. For example, in an analysis of over 225 categories during the period 1987 to 1994, Hoch and Lodish (2001) found that the average annual share of sales for store brands increased by 1.12 percent, while the average shares of the top three national brands in each category fell by 0.20 percent. According to the Private Label Manufacturers' Association (PLMA), store brands now account for one in every five items sold in US supermarkets and represent nearly a $50 billion segment of the retailing business (Hansen et al., 2006). This trend has also occurred in international markets. A striking example is Germany, Europe's largest and the world's third-largest economy. Over the last three decades, store brand share tripled from 12 percent to 34 percent. Worldwide, the six largest retailers obtain between 24 percent and 50 percent of their revenue from store brands, while the tenth-largest retailer, Aldi, stocks its stores almost exclusively with store brands (Kumar and Steenkamp, 2007, p. 3).

* The authors are listed in alphabetical order. The authors thank Marnik Dekimpe, Vincent Nijs, Raj Sethuraman, the editor and an anonymous reviewer for their excellent input and suggestions.

No longer are store brands only for recessionary times, to be discarded once the economy has picked up again (Lamey et al., 2007). Although traditionally store brands were perceived to be low-quality brands and inexpensive versions of generics, they have made great strides in quality in recent years (Quelch and Harding, 1996; Dunne and Narasimhan, 1999). Increasingly, retailers are differentiating themselves and building customer loyalty by offering quality products that are unavailable elsewhere, for example through multi-tiered offerings such as premium versus value store brands (Zimmerman et al., 2007). For instance, *Consumer Reports* magazine ranked Winn-Dixie's chocolate ice cream ahead of Breyers, Wal-Mart's Sam's Choice better than Tide detergent, and Kroger's potato chips tastier than Ruffles and Pringles. At the 2005 annual Christmas wine Oscars in the UK, Tesco Premier Cru, at less than £15 a bottle, was named the best non-vintage champagne. It beat in blind taste tests famous names such as Taittinger and Lanson that can cost twice as much. A German study across 50 consumer product categories (reported in Kapferer, 2003) found that in over half of these categories, the hard discounter store brands (e.g. Aldi, Lidl) rivaled or exceeded the quality of manufacturer brands. A US study (Apelbaum et al., 2003) reports that the average quality of store brands exceeds the average quality of national brands in 22 out of 78 categories. In sum, store brands are becoming largely quality-equivalent to national brands (Soberman and Parker, 2006), although national brand manufacturers have been slow to face up to this new market reality in their planning and marketing decisions (Kumar and Steenkamp, 2007).

From a strategic pricing perspective, three sets of players are affected by store brands and interact to create their net impact: (i) the retailers, (ii) the manufacturers, and (iii) the consumers. For the retailers, store brands typically provide greater (percentage) margins (Hoch and Banerji, 1993; Sayman et al., 2002; Narasimhan and Wilcox, 1998; Pauwels and Srinivasan, 2004). Since store brands by definition can be exclusively sold by the retailer that carries them, many retailers attempt to use this exclusivity to differentiate themselves from the competition (Ailawadi et al., 2008; Walters and Rinne, 1986). Moreover, store brands change the retailer–national brand manufacturer interaction from one of cooperation to one of competition for consumer dollars (Chintagunta et al., 2002). Retailer performance is linked to all the brands in the category (Raju, 1992; Sayman et al., 2002), and, as such, this changing competitive environment may induce reconsideration of how store brands and national brands should be priced. Indeed, categories with larger store brand share tend to get more retailer pricing attention with more extensive use of demand-based pricing rather than past-price dependence and higher-category profits (Nijs et al., 2007; Srinivasan et al., 2008).

For the national brand manufacturers, the growing competitive element in the manufacturer–retailer relationship may change the strategic interaction between the two parties (Mills, 1995; Steiner, 2004). For example, national brand manufacturers may increasingly respond to store brands with changes in regular prices (Hauser and Shugan, 1983) and with changes in price promotions (Lal, 1990; Quelch and Harding, 1996). The advent of 'premium' store brands adds quality competition to the picture and brings the fight from lower-tier national brand to premium-tier national brands (Kumar and Steenkamp, 2007; Pauwels and Srinivasan, 2004). Therefore national brands increasingly find themselves in a battle for market share with their own customers: retailers.

The responses of consumers define the demand side. Store brands often make it more affordable to buy into the category, and thus may increase primary demand, creating

room for win–win scenarios among entrant and incumbent brands (Hauser and Shugan, 1983). Alternatively, the introduction of store brands may result in brand switching, drawing buyers away from the existing brands (Dekimpe et al., 1997; Srinivasan et al., 2000). Moreover, long-term price sensitivity may change due to the different competitive market structure over time.

Given the increasing quality-equivalence between national brands and store brands, they have become direct competitors, and their pricing decisions should take this into account. In most cases, national brands still possess some degree of market power over store brands. In this chapter, we identify the components of such power: (1) price premium, (2) volume premium, and (3) margin premium. We discuss the main drivers of these components and their implications for retailers and national brand manufacturers. To this end, we draw upon the extant literature in marketing and economics on national brands versus store brands.

2. Framework for pricing national brands versus store brands

In industrial economics, a brand is said to have market power when it is able to charge prices exceeding marginal costs (Besanko and Braeutigam, 2005). In a perfectly competitive market, price equals marginal costs, and brands have no market power. However, producers of differentiated products (and monopolists) will, in general, be able to charge prices that exceed marginal costs, and, hence, have market power. In the context of the packaged goods industry, the relative market power of retailers versus manufacturers determines how total channel profit is split between the two (e.g. Kadiyali et al., 2000).

Market power of national brands can arise from a variety of sources. Two natural dimensions are the ability to outprice and outsell the store brand, and can be measured as the price and volume premium, respectively (Ailawadi and Harlam, 2004).

2.1 Price premium

We define the price premium[1] as the difference in price between a specific national brand and a corresponding specific store brand offered by the retailer:

$$Price\ premium_{NB} = Price_{NB} - Price_{SB} \tag{12.1}$$

2.2 Volume premium

We define the volume premium as the difference in the volume between a specific national brand[2] and a corresponding specific store brand offered by the retailer:

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[1] This metric is based on the price premium charged in the market and is not the same as the price premium metric commonly used in the literature. The latter is defined as the maximum price consumers will pay for a national brand relative to a store brand expressed as the proportionate price differential that consumers report that they are willing to pay for a national brand over a private label, and is usually obtained from survey data (Sethuraman and Cole, 1999).

[2] Moreover, it is important to note that typically, only leading national brands in a category command a volume premium over the private label good. For the other national brands in the category, the situation could vary on a case-by-case basis, and the volume premium could well be negative for specific national brands.

$$Volume\ premium_{NB} = Volume_{NB} - Volume_{SB} \tag{12.2}$$

Both retailers and manufacturers consider the likely impact of their pricing decisions on volume premiums, although the many complexities are not yet well understood (Sayman and Raju, 2007).

2.3 Margin premium

Ultimately, retailers and manufacturers should make pricing decisions that optimize their overall profits (Kumar and Steenkamp, 2007; Raju et al., 1995a).

$$Retailer\ margin\ premium_{NB} = Retailer\ profit\ contribution_{NB} - Retailer\ profit\ contribution_{SB} \tag{12.3}$$

$$Manufacturer\ margin\ premium_{NB} = Mfr\ profit\ contribution_{NB} - Mfr\ profit\ contribution_{SB} \tag{12.4}$$

Evidently, the key to price premiums, volume premiums and margin premiums is the price/quality positioning of store brands, in relation to the quality and price of national brands (Sayman and Raju, 2007). Table 12.1 provides a scheme to understand the extent to which three main types of prevalent private label brands, generic private labels, copycat private labels and premium private labels differ in terms of their characteristics from national brands.

Examples of premium-tier (lower-tier) store brands are Sam's Choice (Great Value) and Archer Farms (Market Pantry) at Wal-Mart and Target, respectively. The most common strategy is an imitation or copycat strategy, accounting for more than 50 percent of the store brand introductions (Scott Morton and Zettelmeyer, 2004).

2.4 Illustrative numerical example

To illustrate the problem of pricing store brands versus national brands, we consider the fictional numerical example of a store brand entering a category in a retail store with two incumbent national brands with retail prices of \$2.00 and \$3.00 and wholesale prices of \$1.50 and \$2.00, respectively. In this market, the retailer sells 300 units of each brand, yielding category revenues of \$1500 and a margin of \$450. The retailer considers introducing a store brand that falls into one of the following three categories:

(a) a generic store brand, SB_1 at a price of \$1.50; i.e. lower than any other brand;
(b) a copycat store brand SB_2 at a price of \$2.50; i.e. right in between the national brand prices;
(c) a premium store brand, SB_3, at a price of \$3.00; i.e. at the highest end of the market.

Because of the different quality of the ingredients, these store brand options also differ in wholesale price: \$0.90 for the generic brand, \$1.25 for the copycat brand and \$1.80 for the premium store brand. How will these options impact short-term retailer revenues, manufacturer revenues and category margin? We start from a very simple formal model

Table 12.1 Price premium, volume premium and margin premium of national brand versus store brand

Examples	Characteristics	Illustrative papers	Price premium	Volume premium	Margin premium
Generic store brands	No brand name products Example – generic sugar	Steenkamp and Kumar (2007)	Large; sell 20%–50% below national brand	Moderate to high, depending on price sensitivity of potential customers	High; they have a very low price and suffer from low margins relative to national brands
Copycat brands	Me-too brand copying a strong brand leader Example – Walgreens Shampoo	Pauwels and Srinivasan (2004) Soberman and Parker (2006) Sayman et al. (2002)	Moderate; 5%–25% below national brand	Moderate to low, depending on the copycat execution and the loyalty for the emulated brand	Moderate; their cost structure is similar to imitated national brands
Premium store brands	Premium store brand offered as best products on market Example – Archer Farms (Target)	Corstjens and Lal (2000) Steenkamp and Kumar (2007)	Zero or even negative; sometimes priced higher than national brands	Moderate to high, depending on the retailer's ability to convince consumers of premium-tier status	Moderate to low; critically depends on sales success given similar retail and wholesale price

to derive the initial effect on sales and margin. Consider the Hotelling competitive positioning model in which consumers are uniformly distributed in their ideal points for quality/price positions (e.g. Lilien et al., 1992, p. 233). Figure 12.1 visualizes our pre-entry situation, in whom the incumbent national brands split the current number of shoppers for whom the buying utility exceeds the price of second-tier national brand NB_1. All shoppers to the left of this point X_1 do not buy in the category (i.e. the 'outside good'), while all customers to the right of point X_2 prefer the premium national brand NB_2. As usual in this model, we assume complete information (i.e. full consumer awareness/knowledge of all brands and perceived quality equals objective quality).

What happens when a store brand gets introduced into this market? When the retailer enters with the generic store brand SB_1, it expands the category by moving X_1 to the left (from X_1 to X_1'). Moreover, it steals share from NB_1, not from NB_2. In contrast, entering with the copycat SB_2 does not expand the category. Instead, the introduction steals share from both NB_1 and NB_2. Finally, premium-tier brand SB_3 competes directly with the premium national brand NB_2 and steals share from it. Table 12.2 calculates how the three options differently impact key performance indicators for retailers, consumers and manufacturers.

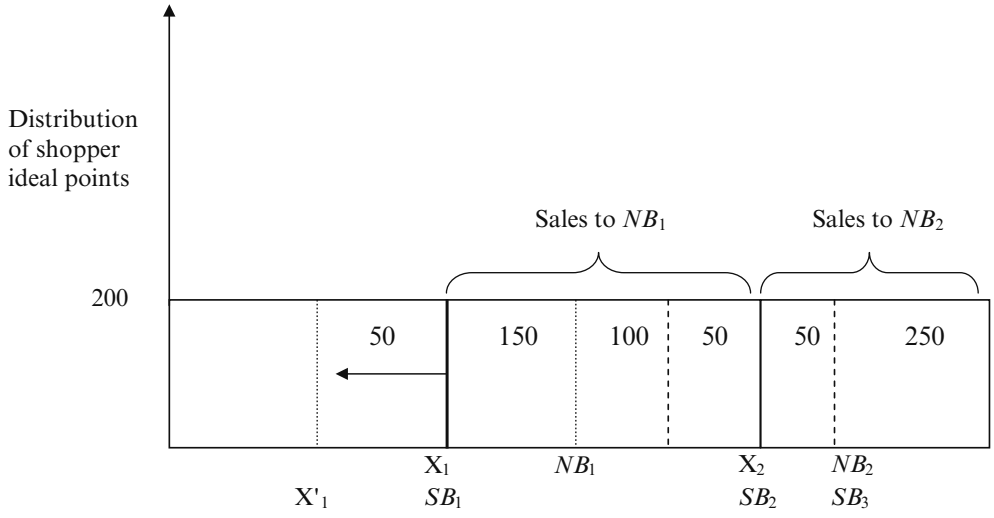

Figure 12.1 Simple model of sales of national brands versus store brands

2.4.1 Retailer's perspective When the generic store brand SB_1 is introduced, it obtains 200 customers and a healthy margin of \$120. For the total category, demand grows from 600 to 650, and retailer gross margin increases from \$450 to \$495. In contrast, the copycat store brand does not expand category demand and obtains a smaller customer base (100), but with a higher store brand margin of \$125. Category margin grows to \$500. Finally, the premium store brand does not expand demand but obtains a customer base of 150 and obtains the highest store brand margin (\$180). However, retailer category margin increases only to \$480. Thus it appears that in this case, the copycat store brand strategy yields the highest contribution to retailer profits. The important point is that this revelation of the optimal store brand strategy for the retailer requires a category management perspective; it would not derive from a simple assessment of the sales and margin contribution of the store brand itself. Indeed, the generic store brand is the clear winner in terms of store brand sales and category traffic, while the premium option yields the highest margin from the store brand itself.

2.4.2 Consumer's perspective From the consumer's perspective, the average price before the introduction is \$2.50. This average price stays the same for the copycat and premium store brand options but lowers to \$2.30 with the introduction of the generic store brand. Thus price-sensitive shoppers, in particular those that now become new-category customers, benefit from the generic store brand introduction, leading to category expansion. No such benefit occurs for the copycat brand and, in our example, for the premium store brand. We return later to possible store loyalty effects of high-quality store brands.

2.4.3 Manufacturer's perspective Store brand entry hurts the sales of at least one national brand in our example, with the extent of the damage depending on store brand price/quality positioning. Would supplying the store brand overcome the margin loss for

Table 12.2 Illustrative example on pricing of national versus store brands

Variable	Retailers			Manufacturers	
	Store brands			National brands	
	SB_1	SB_2	SB_3	NB_1	NB_2
Retail price	\$1.50	\$2.50	\$3.00	\$2.00	\$3.00
Wholesale price	\$0.90	\$1.25	\$1.80	\$1.50	\$2.00
Manufacturer cost	\$0.70	\$1.00	\$1.50	\$1.00	\$1.50
Before introduction					
Sales				300	300
Manufacturer revenue				\$450	\$600
Retailer revenue				\$600	\$900
Retailer margin				\$150	\$300
Category sales = 600, retailer category revenues = \$1500, retailer category margin = **\$450**					
After introduction of SB1 (generic store brand)					
Sales	200			150	300
Manufacturer revenue	\$180			\$225	\$600
Retailer revenue	\$300			\$300	\$900
Retailer margin	\$120			\$75	\$300
Category sales = 650, retailer category revenues = \$1500, retailer category margin = **\$495**					
After introduction of SB_2 (copycat store brand)					
Sales		100		250	250
Manufacturer revenue		\$125		\$375	\$500
Retailer revenue		\$250		\$500	\$750
Retailer margin		\$125		\$125	\$250
Category sales = 600, retailer category revenues = \$1500, retailer category margin = **\$500**					
After introduction of SB_3 (Premium store brand)					
Sales			150	300	150
Manufacturer revenue			\$270	\$450	\$300
Retailer revenue			\$450	\$600	\$450
Retailer margin			\$180	\$150	\$150
Category sales = 600 retailer category revenues = \$1500, retailer category margin = **\$480**					

the national brand manufacturer? This appears unlikely given the competitive nature of the store brand procurement market (Kumar and Steenkamp, 2007). In all of our scenarios, the manufacturer margin on the national brand remains higher than that for the store brand (which is \$40, \$25 and \$45). Table 12.3 shows the components of price premium, volume premium and retailer margin premium of each national brand over the three store brand options.

Even in this stylized example, the observed scenarios are relatively complex: national brands may have positive or negative price premium, volume premium and margin premium over a store brand. And, of course, actual markets involve several issues that further influence the impact of store brands, including (1) varying retailer success in bridging the gap between perceived versus objective store brand quality, (2) consumer

Table 12.3 Illustrative example on pricing of national versus store brands

Examples	Price Premium	Volume Premium	Margin Premium
After introduction of SB_1 (generic store brand)			
Second-tier national brand (NB_1)	\$0.50	−50	−\$45
Premium-tier national brand (NB_2)	\$1.50	100	\$180
After introduction of SB_2 (copycat store brand)			
Second-tier national brand (NB_1)	−\$0.50	150	\$0
Premium-tier national brand (NB_2)	\$0.50	150	\$125
After introduction of SB_3 (premium store brand)			
Second-tier national brand (NB_1)	−\$1.00	150	−\$30
Premium-tier national brand (NB_2)	\$0.00	0	−\$30

involvement with and perceived risk in the category and (3) national brand manufacturers' reaction in terms of product, price and advertising. We next turn to these drivers of the premium components.

3. Findings on pricing of national brands versus store brands

Despite the high and increasing importance of store brands for both retailers and manufacturers, we have seen relatively little academic research on pricing of national brands versus store brands. This is probably because of the mindset of both marketing academicians and executives in manufacturer companies, who tend to consider store brands as inferior goods and hence focus on competition between national brands (Kumar and Steenkamp, 2007). As a result, we believe it is too early to give exact recommendations on how to price national brands versus store brands. However, as argued, this decision will depend on the three components of market power. The last two decades have yielded influential articles on the importance, presence and drivers of the three premiums mentioned, as shown in Table 12.4.

Table 12.5 shows how the various drivers influence price, volume and margin premiums, and also offers some generalizations on these effects in the last column. Clearly, this is an area where more research is needed to make specific predictions on pricing, so we conclude in Section 4 with suggestions for future research.

3.1 Price premium

3.1.1 Importance The price premium of a national brand over a store brand is of major importance to both manufacturers and retailers (Hoch and Banerji, 1993). In the absence of pricing mistakes, it reflects consumer willingness to pay for the different brands. For manufacturers, keeping consumer prices high is a main objective. Consider the typical economics of a S&P500 company (Kumar and Steenkamp, 2007): 19.2 percent of all revenues are needed to cover fixed costs, 68.3 percent to cover variables costs, leaving a profit margin of 12.5 percent. All other things equal, a price increase of 2 percent would

Table 12.4 Illustrative papers on price, volume and margin premiums

Paper – authors/ year of study	Substantive issue	Data	Key contribution
1. Price premium			
Raju et al. (1995a)	Decision to introduce a store brand into a category	IRI data on 438 product categories	Store brands are more likely to be introduced in categories where the price competition is low, and when the number of national brands is high.
Raju et al. (1995b)	Price differential of national brands	Numerical simulations of data	Results show that a store brand can obtain a high market share even with a low price differential when the cross-price sensitivity is high.
Hoch and Lodish (2001)	Optimal price gap	Two consumer studies and two in-market pricing tests	Most retailers would improve profits by maintaining national brand pricing and closing the gap by raising store brand prices.
Sethuraman and Cole (1999)	Factors influencing the price premium	Random survey of 350 households	Perceived quality differential is the most important driver of price premiums.
Apelbaum et al. (2003)	Extent to which quality premiums drive price premiums	*Consumer Reports* data for 78 product categories	For 75% of the categories considered, the average quality of national brands was higher than that of store brands, and price premiums for national brands prevail regardless of their command of quality premium or not.
Sayman et al. (2002)	Retailer's store brand positioning problem	Data from 19 product categories	In categories with high-quality store brands, the store brand and the leading national brand compete more intensely with each other than with the secondary national brand.
2. Volume premium			
Hoch and Banerji (1993)	Cross-category differences in private label share	185 grocery categories	Six variables (quality relative to national brands, quality variability, category revenue, percentage gross margins, number of national brand manufacturers, and national advertising expenses) explain 70% of the variance in market shares.
Dhar and Hoch (1997)	Store brand penetration variations across retailers	34 food categories for 106 major chains	Store brand penetration increases with retailer size, commitment to quality, category expertise, the use of own name on the store brands, breadth of store brand offerings, premium store brand offerings, and promotional support for the store brand.

Table 12.4 (continued)

Paper – authors/ year of study	Substantive issue	Data	Key contribution
Hansen et al. (2006)	Drivers of store brand purchase across categories	10 food and non-food product categories	Household-level traits which are no-category-specific explain variation in store brand shares across categories.
Cotterill et al. (2000)	Factors that drive market shares of private label brands	143 food categories in 59 geographic markets	Feature and display promotions are more effective than price cuts for private labels to gain share from national brands.
Deleersnyder et al. (2005)	Factors that drive national brand success	400 brands in 6 stores in 3 countries	Large price gaps benefit both manufacturers and retailers since they signal that the brands are targeted at different consumers/ purchase occasions.
Erdem et al. (2004)	Factors that drive store brand shares	Scanner data for 3 countries (UK, USA, and Spain)	Quality uncertainty is the key determinant of store brand market share across countries, more important than price sensitivity.
3. Margin premium			
Ailawadi and Harlam (2004)	The effect of store brand share on margins of the retailer	Retail data from a grocery and a drug retail chain for multiple categories	Retailers' percentage margin on store brands is higher than on national brands, even though dollar margin per unit may be lower for store brands.
Pauwels and Srinivasan (2004)	Impact of store brand entry on retailer margins	Data from 4 food and non-food categories with store brand entry	Store brand entry raises retailers' margins due to high unit margins on the store brand as well as on the national brands.
Ailawadi et al. (2008)	Impact of store brand use on store loyalty	Consumer hand-scan panel: all categories	Store brand use and store loyalty (share of wallet) have an inverted U-shaped relationship.

thus raise profits by 16 percent, and vice versa. Evidently, the net effect will depend on the resulting volume changes, and manufacturers need to understand both own and cross-price elasticities in the market, including that of their brand with the store brand. For retailers, the price premium, also known as the price gap between a national brand and the store brand, is a key driver of the gross dollar margin from the store brand, but also of the total category's profit to the retailer. Papers in economics have argued that the magnitude of the ratio of national brand to store brand prices can be used to measure the markup of the retailer (Scherer and Ross, 1990; Carlton and Perloff, 1994; Barsky et al., 2001).

3.1.2 Presence In all studied countries, even those leading in store brand quality and penetration, a price premium still exists between national brands and store brands

Table 12.5 Generalizations on drivers of price premiums, volume premiums and margin premiums

Premium components	Drivers	Illustrative papers	Generalization
A. Price premium	Perceived quality	Sethuraman and Cole (1999); Hoch and Banerji (1993); Apelbaum et al. (2003)	Brands with higher perceived quality command higher price premiums.
	Innovation	Pauwels and Srinivasan (2004); Steiner (2004)	Innovative national brands command higher price premiums.
	Imagery/feelings	Wills and Mueller (1989); Connor and Peterson (1992)	Brands high on imagery command higher price premiums.
	Promotional activity	Cotterill et al. (2000)	Higher price promotional activity in a category leads to lower price premiums.
	Category characteristics	Ailawadi et al. (2008); Steenkamp and Dekimpe (1997)	Category characteristics are related to price premiums.
	Retailer store brand strategy	Meza and Sudhir (2002); Soberman and Parker (2006)	Price premiums of national are largest vs generic store brands, followed by copy-cat brands and least vs premium store brands.
B. Volume premium	Prices of national vs private labels	Dhar and Hoch (1997); Hoch and Lodish (2001); Geyskens et al. (2007)	Negative impact for within-category changes; positive impact across categories as high-selling store brands allow the retailer to charge more.
	Availability of brands	Srinivasan et al. (2004); Ailawadi et al. (2008); Kumar and Steenkamp (2007)	Availability of popular national brands drives volume premiums.
	Usage occasions	Pauwels and Joshi (2007)	Volume premium depends on usage occasions.
C. Margin premium	Wholesale prices	Ailawadi (2001); Sethuraman (2006); Ailawadi and Harlam (2004)	Higher wholesale prices of national brands result in lower margin premiums.

Table 12.5 (continued)

Premium components	Drivers	Illustrative papers	Generalization
	Price premiums	Pauwels and Srinivasan (2004); Kumar and Steenkamp (2007)	Factors that drive the price drive premium of the national brand will margin premiums.
	Brand switching patterns	Pauwels et al. (2007); Rangan and Bell (2002)	Retailer gross margin depends on the switching patterns among brands.
	Category expansion and store traffic	Bronnenberg and Mahajan (2001)	Category expansion and store traffic effects of enhanced retailer profitability for store brands.
	Store image	Corstjens and Lal (2000)	Store brands enhance store image and retailer margins.

in general (Pauwels and Srinivasan, 2004; Dhar and Hoch, 1997). Based on IRI (Information Resources Inc.) pricing data, the current price premiums across all US retailers between national and store brands is about 25–30 percent (Hoch and Lodish, 2001). Kumar and Steenkamp (2007) report an average price premium of 37 percent in situations where the store brand is quality-equivalent with the national brand. Moreover, Apelbaum et al. (2003) report a 29 percent price premium in categories where average store brand quality exceeds average national brand quality and a 50 percent price premium in other categories. However, this price premium appears under siege. For instance, a recent survey by AC Nielsen (2005) revealed that only 29 percent of US consumers agree that manufacturer brands are worth the price premium. Several driving forces may explain why the price premium has been going down over time (Kumar and Steenkamp, 2007).

3.1.3 Drivers of price premium In general, consumers compare the price of a product to the utility they derive from buying and consuming it. This utility may have both rational and emotional components, also known as performance perceptions and judgments versus imagery and feeling in the customer-based brand equity framework (Keller, 1993). Research has shown that the range of acceptable prices depends on the product characteristics such as brand familiarity (Monroe, 1976) and on customer perceptions of price and value (Raju et al., 1995b).

DRIVER 1: PERCEIVED QUALITY Branded and private label versions of a product cannot be identical, as that would violate the law of one price (Barsky et al., 2001). Despite the increasing quality-equivalence of national brands and store brands in general, certain national brands do succeed in maintaining superior perceived quality. Perceived quality of the national brand versus the store brand is a key driver of the price premium because

most consumers care more about quality than about price (Steenkamp, 1989; Sethuraman and Cole, 1999; Hoch and Banerji, 1993). French data revealed that in categories where manufacturer quality exceeds store brand quality, the price premium for national brands is 56 percent; in quality-equivalent categories, it is 37 percent; and in categories where store brand quality is higher, the price premium is 21 percent (Kumar and Steenkamp, 2007). In the USA, the numbers are similar: quality-equivalence yields a 37 percent price premium for national brands, and a 1 percent quality gap results in a 5 percent price gap (Apelbaum et al., 2003). Therefore both national brand manufacturers and retailers should carefully monitor the perceived quality of their brands. In fact, empirical evidence suggests that as store brands improve their quality, national brands lose some of the pricing power, and the price premium they command relative to the store brand decreases (Rao and Monroe, 1996). If the manufacturer fails to convince consumers of its higher quality, it is tough to justify a high price premium. Likewise, if the retailer fails to convince quality-sensitive consumers of its high store brand quality, it is left with only the price-sensitive buyers and consequently has to charge a lower price for its store brand. This is especially true when consumers believe it is only fair that the store brand charges them less because it costs less to the retailer, for instance because of the lower quality of the ingredients. Interestingly, though, quality is not the full story: US consumers perceive store brands to be quality-equivalent in 33 percent of cases, but are only willing to pay the same price in 5 percent of all cases (AC Nielsen, 2005).

DRIVER 2: INNOVATION Besides enhanced quality, national brands may also contain desirable new features that are not (yet) present in store brands. For instance, Pauwels and Srinivasan (2004) find that, faced with store brand entry and resulting price competition at the low end of the market, some manufacturers take the high road and introduce innovative, higher-priced SKUs (stock-keeping units). In contrast, due to their reliance on low prices, store brands are not typically engaged in expensive product innovations, and thus score low on innovativeness (Steiner, 2004). As such, a highly innovative national brand will clearly stand out and be able to command a higher price premium (Deleersnyder et al., 2007). In contrast, categories with few national brand innovations allow the store brand to easily close the quality and price gap (Hoch and Banerji, 1993).

DRIVER 3: IMAGERY/FEELINGS The emotional components of product utility are known under many labels: brand feelings, image, emotional bond, love, engagement, etc. National brand manufacturers use their large advertising budgets and brand-building experience to create and sustain these elements of brand equity. Specifically, research has found that advertising has a positive effect on the price of national brands relative to store brands (Wills and Mueller, 1989; Connor and Peterson, 1992). Kumar and Steenkamp (2007) report that the typical price premium for brand image is 23 percent. In France, categories high on imagery obtain an average price premium of 61 percent compared to only 38 percent in categories low on imagery. However, creative marketing can and has achieved high image in such categories as baked beans and paper towels (ibid.). While such imagery used to be generated by television advertising, future success may be more readily obtained through such new communication channels as videogame marketing, 'underground marketing' (e.g. Red Bull giving free samples to trendsetting people and bars, but refusing them to others), word-of-mouth marketing, Internet

community marketing (e.g. Trusov et al., 2007), and the like. Manufacturers appear to have a substantial advantage over retailers in this regard. Once retailers move beyond simple copycat strategies for their store brands, they may find creative ways to build their own imagery components, instead of merely attempting to demote the imagery of national brands.

DRIVER 4: PROMOTIONAL ACTIVITY While non-price-oriented promotions by national brands may benefit their price premium, price-oriented promotions appear 'fast but faulty'. In the short run, price promotions may enable national brands to keep price-sensitive consumers from trying store brands (e.g. Lal, 1990) and thus help sustain their price premium at regular levels. In the long run, however, price promotions may teach consumers to 'lie in wait' for deals (Mela et al., 1997) and focus on price instead of quality as a buying criterion (Kalwani and Yim, 1992; Wathieu et al., 2004). Moreover, price promotional activity in a category not only lowers prices but is also a more effective way for store brands to gain share from national brands (Cotterill et al., 2000).

DRIVER 5: CATEGORY CHARACTERISTICS Despite increasing quality and consumer acceptance of store brands, willingness to pay for them still varies substantially by category (Steenkamp and Dekimpe, 1997; Ailawadi et al., 2008). The first author of this chapter analyzed a European dataset where the price premium of the store band versus the leading national brand varied from virtually zero (e.g. aluminum foil and canned vegetables) to over 80 percent (e.g. shampoo and bodymilk). These variations in price premium were associated with consumer involvement with the category: the price premium is higher for categories that connect to consumers' ego and self-image (Assael, 1998), with higher hedonic value (Holbrook and Hirschman, 1982), and with a higher social expressive or sign value (McCracken, 1986). Other important characteristics may include the risk and credence nature of the product category.

DRIVER 6: RETAILER SIZE AND STRATEGY First, retail consolidation reduces the price premium of national brands (Cotterill et al., 2000). Second, we know that the price premium of national brands depends on the store brand strategy of the retailer. Kumar and Steenkamp (2007) show that 'generic store brands' and 'value innovators' have a large discount (20–50 percent), 'copycat' brands have a moderate discount (5–25 percent) compared to brand leaders, while 'premium store brands' are priced close to or higher than the brand leaders. Recent research suggests that when it comes to copycat store brands, retailers may behave non-optimally by increasing the price of the national brand imitated by the store brand and by maintaining a high price differential between the copycat store brand and the national brand (Meza and Sudhir, 2002; Soberman and Parker, 2006). Importantly, 'despite all the buzz surrounding premium store brands, we should not forget that traditional store brands – generics and copycats– are still the dominant types of store brands around the world' (Kumar and Steenkamp, 2007, p. 29). Even so-called 'premium' store brands are typically not 'premium-price' (priced above leading manufacturer brands) but 'premium-lite', i.e. of similar/higher quality than manufacturer brands but at a lower price. Moreover, even truly premium-price retailer brands are still necessarily mass-market, and consequently may be priced below a niche manufacturer brand. Increasingly, retailers maintain a portfolio of store brands similar to Tesco's

three-tier strategy (Buckley, 2005): low-priced Tesco Value (lowest price: 34 percent of its store brand volume), Tesco (standard quality: 61 percent of its store brand volume), and Tesco's Finest (highest quality: 5 percent of its store brand volume).

3.2 Volume premium

3.2.1 Importance Because manufacturers face substantial fixed costs (on average, 19 percent of revenues at full capacity), it is very important to keep volumes up and, thus, keep factories running. Higher volumes also mean better bargaining power with suppliers and with retailers, who prefer to stock and promote leading manufacturer brands (e.g. Pauwels, 2007). Retailers care about volume for similar scale and scope reasons, and several studies have investigated factors that lead to successful store brands (Hoch and Banerji, 1993; Dhar and Hoch, 1997; Hoch et al., 2002).

3.2.2 Presence In the USA, the leading national brand typically still has a volume premium over the store brand, but this is no longer true in several categories and in several European countries. Kumar and Steenkamp (2007) project a store brand share of 40–50 percent: increasing retailer consolidation and globalization will increase current store brand shares, but after a certain point, higher store brand share will turn off consumers looking for choice and will not be beneficial to the retailer (Ailawadi et al., 2008). Still, an expected store brand share of 40–50 percent implies a substantial loss of volume premium, as has been demonstrated across 225 consumer-packaged goods categories in Hoch et al. (2002), who find that store brands capture most of the category growth and steal away share, especially from the smaller national brands.

3.2.3 Drivers of volume premium Evidently, the volume premium may be affected by the same drivers as those identified for price premium. Additional drivers include prices, availability and usage occasions as detailed below.

DRIVER 1: PRICES OF NATIONAL BRAND AND STORE BRAND The relation between the price gap and store brand sales depends on whether one considers within-category effects (over time) versus cross-category relations (Raju et al., 1995b; Sayman and Raju, 1997). Focusing on within-category effects, research finds that a 10 percent change in the price gap fraction results in a 0.8 percent change in the store brand share (Dhar and Hoch, 1997). In contrast, cross-category comparisons find a higher store brand share with a smaller price gap (Mills, 1995; Sethuraman, 1992), apparently because store brand popularity in a category allows the retailer to price it close to the national brands (Raju et al., 1995b). Moreover, Dhar and Hoch (1997) argue that a high price differential leads (some) consumers to infer that the store brand has substantially lower quality, outweighing the positive direct price effect. The situation gets more complex in the presence of compromise, similarity and attraction effects (e.g. Geyskens et al., 2007).

DRIVER 2: AVAILABILITY Distribution is a key driver of store brand share and growth (Dhar and Hoch, 1997; Kumar and Steenkamp, 2007; Sayman and Raju, 2007). Indeed, European store brands may derive their strength from championing by large, consolidated retailers (Hoch and Banerji, 1993) versus smaller manufacturers. However, even

the largest retailer is not the only game in town and thus typically fails to obtain the quasi-universal availability of popular national brands. This provides an important edge to national brands, which they should strive to maintain. In principle, retailers could overcome this advantage by either licensing their store brands to other retailers (e.g. President's Choice) or creating such a strong preference for their store brands that most consumers will seek them out at the expense of other retailers. With a few notable exceptions, either scenario appears unlikely. Licensing to competitors reduces the differentiation a retailer achieves with its store brand, and price-sensitive shoppers tend to look intelligently for deals wherever they are and thus are 'loyal' to store brands in general rather than to the store brand of a specific retailer (Ailawadi et al., 2008). Related to the retailer distribution strength, research has shown that the higher the retailer's private label share in a category, the lower the revenue benefits a national brand obtains from its own promotions (Srinivasan et al., 2002; 2004).

DRIVER 3: RETAILER POSITIONING Dhar and Hoch (1997) find that store brand penetration increases with retailer commitment to quality, category expertise, the use of own name on the store brands, premium store brand offerings and promotional support for the store brand.

DRIVER 4: USAGE OCCASIONS As long as consumers associate certain usage occasions with certain brands, the volume premium also depends on the frequency of such usage occasions. For one snack category, Pauwels and Joshi (2007) find that 'entertaining friends' and 'afternoon lift' occasions were associated with the national brand. However, the typical 'store brands for myself, national brands for conspicuous consumption' attitude is not set in stone, as consumers in some countries (such as Germany, the UK and the Netherlands) proudly display their smart, best-value shopping (Kumar and Steenkamp, 2007). Even in the USA, only 6 percent of consumers feel uncomfortable serving store brands in their homes (AC Nielsen, 2005). Therefore, to safeguard their volume premium, manufacturers may strive to 'set the agenda' in terms of usage occasions and their link to the national brand.

3.3 Margin premium

3.3.1 Importance The manufacturer margin premium is especially important if a given manufacturer is (or is considering) supplying both national brands and store brands (Kumar and Steenkamp, 2007). The retailer margin premium is obviously relevant to retailers, as they want to carry the optimal assortment of brands to maximize their overall profitability. Moreover, national brand manufacturers need the retailer's cooperation for a host of activities that affect the national brand's performance: sufficient and appropriately located shelf space, promotional pass-through, launch and promotion of new products, etc. Negotiations on such activities are easier when the manufacturer can demonstrate and quantify the contribution of these activities to the retailer's profitability.

3.3.2 Presence Little is known about the margin premium for national brand manufacturers, mostly because they do not spread the word that they are also producing store brands (Kumar and Steenkamp, 2007). Therefore the presence and drivers of this

manufacturer margin premium are a key topic for future research. In contrast, it is now well documented that store brands give retailers a better percentage margin than national brand manufacturers do (Ailawadi and Harlam, 2004; Handy, 1985; Hoch and Banerji, 1993). Sethuraman (2006) reports that the average retailer's margin from store brands is about 34 percent compared to the margin of 24 percent that retailers obtain from national brands. However, virtually unanswered is the more relevant question about how much each brand contributes to the category's gross margin and to retailer overall profitability (Ailawadi and Harlam, 2004; Ailawadi et al., 2008). Several factors need to be considered to determine each brand's margin contribution to the retailer, and our numerical example in Section 2 and recent research demonstrates that the margin premium may substantially vary depending on several drivers.

3.3.3 Drivers of margin premium

DRIVER 1: WHOLESALE PRICES Wholesale prices are almost always lower for store brands, even compared to small national brands (e.g. Sethuraman, 2006; Ailawadi and Harlam, 2004). The key reasons are the competitive nature of the store brand procurement market and the much lower marketing and advertising costs faced by store brands as compared to national brand manufacturers. As to the competitive nature of the market, most store brand suppliers are fairly small companies, especially compared to their retail customers. They specialize in a few product categories, product differentiation is virtually absent, optimal scale of production is low, and they sell their products to powerful, well-informed, professional retail buyers. Furthermore, the marketing and advertising costs are much higher for national brands, as they are building consumer-based brand equity (Keller, 1993) by creating and maintaining awareness, relevance and differentiation in consumers' minds.

DRIVER 2: RETAIL PRICES As long as national brands sell at higher retail prices than store brands, their unit dollar margins may be higher even if their percentage margins are lower than the store brands'. Indeed, real-life cases (e.g. Rangan and Bell, 2002) and our numerical example illustrate the situations in which the dollar margins of the store brand are lower than those of at least one national brand: the generic store brand has only a \$0.60 margin as compared to \$1.00 for the premium national brand. Evidently, retail prices depend both on the pricing decisions of the retailer and on consumer willingness to pay for a brand. Often, the dollar margin on the store brand is higher than on that of second-tier national brands – especially if the retailer decides to drop its retail prices in the face of store brand growth (Pauwels and Srinivasan, 2004). Likewise, factors that drive the price premium of the national brand, such as innovation and advertising, will help maintain retail prices and thus dollar margins. On the other hand, the dollar margin benefit erodes with successful retailer efforts to increase willingness to pay for the store brand. Moreover, retailers may further reduce their store brand costs in terms of logistics, rental, overhead, marketing, personnel, etc. 'Value innovator' store brands like Aldi's are especially successful in lowering process costs by passing on shopping functions to the consumer and focusing on a limited assortment to compensate for lower dollar margin with high turnover and supply chain negotiating power (Kumar and Steenkamp, 2007).

DRIVER 3: BRAND SWITCHING PATTERNS Given the tradeoffs in dollar margins, retailer gross margin in the category will critically depend on the switching patterns among brands. Every purchase going from a higher dollar-margin national brand to the store brand will actually reduce retailer gross margin (and related measures such as profit per square foot). Such a situation creates an interesting dilemma for the retailer: if the store brand does not expand category consumption, its sales growth at the expense of national brands may lower total category retail margin. This realization induced HEB Foods managers to consider cheaper sourcing and to reposition the store brand against a low-margin instead of a high-margin national brand (Rangan and Bell, 2002). More generally, both retailers and manufacturers influence these brand-switching patterns. Retailers often emulate a specific national brand (e.g. the brand leader as recommended in Sayman et al., 2002) and promote direct comparison by shelf placement, displays, features, etc. Manufacturers choose to get closer to or further away from the store brand by introducing new products with similar or very different features from those of the store brand (Pauwels et al., 2007) and by pricing their brand closer to or further away from the store brand (Pauwels and Srinivasan, 2004).

DRIVER 4: CATEGORY EXPANSION AND STORE TRAFFIC Besides inducing brand switching within the category, store brands may also induce shoppers to buy in the category or even to come into the store – thus enhancing retailer store profitability. Traditionally, popular and expensive national brands are believed to be more successful in doing so (Bronnenberg and Mahajan, 2001; Pauwels, 2007); witness the loss-leaders in key retail categories. Likewise, Kumar and Steenkamp (2007) note that the velocity (or shelf-space turnover) of national brands is typically 10 percent higher than that for store brands. As a result of the above factors, recent papers argue that store brands are not as profitable as national brands (Corstjens and Corstjens, 1995). A private Price Waterhouse study commissioned by Pepsi in Canada showed that the national brand is typically more profitable than store brands once all factors, including deal allowances, warehousing, transportation and in-store labor were accounted for (Corstjens and Lal, 2000).

However, store brands clearly have the potential to increase category demand and store traffic. As to the former, low-end store brands make the category affordable to budget-restrained shoppers, while premium store brands may attract shoppers who value their quality and/or unique features (e.g. Tesco's Finest). As to the latter, Corstjens and Lal (2000) argue that retailers can attract shoppers with quality store brands, and they report that store brand penetration is positively related to store loyalty and customer share of wallet at the chain. Moreover, Sudhir and Talukdar (2004) find that a household buying store brands in more categories spends more at the store. In contrast, Uncles and Ellis (1989) question the role of store brands in store loyalty, and Richardson (1997) finds no evidence of store brand differentiation in five product categories. A recent study accounts for reciprocity and nonlinearities in the relationship between store brand buying and store loyalty for all categories of a leading supermarket chain (Ailawadi et al., 2008). Their analysis finds that the relationship is inverted U-shaped, with the highest benefits to store loyalty at around 40 percent of store brand share. Stores with lower store brand shares may thus increase store loyalty by pushing their own brands, but only up to a point. Anecdotal evidence suggests that pushing store brands (especially in terms of shelf space) at the expense of national brands may generate a backlash from consumers who value

freedom of choice (ibid.). In sum, the ability of either national brand or store brand to bring in truly new purchases depends not just on their individual consumer appeal but also on the current ratio of consumer purchases and shelf space devoted to store brands.

DRIVER 5: STORE IMAGE At the category level, US consumers still believe that manufacturer brands are better than store brands in 89 percent of categories (Aimark, 2006). In general, the introduction of store brands with high objective quality may be beneficial to the retailer even if there is no margin advantage for the store brand because quality store brands increase store differentiation (Corstjens and Lal, 2000). Just like manufacturers, some retailers spot a 'hole in the market' for a product with a unique feature currently not offered by competitors. For instance, Tesco is able to offer freshly squeezed orange juice in its stores, which is not logistically feasible for the likes of Tropicana and Minute Maid (Kumar and Steenkamp, 2007). Retailers do not compromise on quality of store brands because they cannot really afford to put their store name or their own brand name on a product that is inferior (Fitzell, 1998). For example, if Dominick's were to use its name on a product that is inferior, there would likely be a negative spillover effect on all products and stores carrying that label.

3.4 Pricing implications

3.4.1 What is the preferred price gap for the manufacturer? It differs for premium versus second-tier brands, which face different own and cross-price elasticities with the store brand. This is graphically illustrated by Kumar and Steenkamp (2007, p. 202) and empirically demonstrated in Pauwels and Srinivasan (2004). First, premium brands get a substantially smaller sales increase from a price drop because their customers are more niche and less price-sensitive. At the same time, a price cut from the store brand won't affect them much, either. The recommendation is to keep prices high while justifying the price premium by continuous improvement in the identified drivers of market power (quality, imagery, innovation, association with specific usage occasions, category and store traffic drawing power). Moreover, the manufacturer can add a low-end brand to fight the store brand (e.g. P&G added Mister Clean detergent to its leading Ariel brand in Germany). Second-tier brands face a tough dilemma: they typically cannot win a price war with the store brand, so such brands need to choose between upgrading the brand (a large and uncertain investment) versus head-on value competition with the store brand. The latter strategy is impeded by the absence of the true leverage that national brand manufacturers possess to determine the price gap with store brands: while they can set recommended prices and send consumer coupons, the retailer decides on promotional pass-through and may engage in 'price shielding' by promoting the store brand at the same time (Hoch and Lodish, 2001). In some cases, the manufacturer may be better off divesting in such second-tier brands to focus its resources on a portfolio of leading brands. Unilever, for instance, decided to cut 75 percent of its brands because it had insufficient brand power, defined as the potential to be number one or two in its market and to be a must-carry brand to drive retailer's store traffic (Kumar, 2004).

3.4.2 What is the preferred price gap for the retailer? Answering this question requires knowledge of the performance criterion for the retailer. If only store brand volume is of

interest, larger price gaps may yield more immediate success even though smaller price gaps, accompanied by the necessary investments in store brand quality and the communication thereof, should yield higher sales in the long run (Dhar and Hoch, 1997). Moreover, as argued earlier, store brand volume is only part of the retailer profitability equation. Therefore retailers need to consider the effect of the price gap on category revenues and gross margin. If the price gap is too big, the retailer may lose both manufacturer brand revenue and store brand revenue! In a rigorous field experiment, Hoch and Lodish (2001) found that increasing the price gap from 33 percent to 50 percent for analgesics increases category sales units but reduces revenue as the price elasticity for store brand is low: −0.56. In summary, we obtain consistent advice for retailers aiming to increase (long-run) store brand sales and category performance: strive for smaller price gaps. To this end, the above-identified drivers suggest that retailers should strive to reduce the gap in (perceived) quality, innovation and imagery; increase the store brand's availability and associated usage occasions; and position store brands to expand the category, improve store image, and thus, traffic and basket size in the chain (van Heerde et al., 2008).

In principle, the retailer can manipulate the price gap by changing the retail price of either the store brand or the manufacturer brands. However, the latter is often not a realistic option: increasing national brand prices may induce shoppers to buy them at other retailers, and reducing national brand prices eats away the retailer's margin on them unless the retailer can negotiate for lower wholesale prices. If store brand purchases are being driven by the price component only to a small degree, then the retailer can lower the price gap between the store and national brand and improve profitability (Hoch and Lodish, 2001). In order to do so, the retailer would have to know the answer to the question of which store brand purchases are being driven by brand preferences versus price considerations (Hansen et al., 2006).

4. Future research directions

Our review has emphasized the role of price premium, volume premium and margin premium in national brands versus private label brands. As Table 12.4 indicates, empirical work in this area has been expanding rapidly. These previous studies have dealt primarily with understanding the drivers of price premium or volume premium for national brands versus store brands. Recently, however, we have witnessed research in this area addressing a new set of strategic questions on national brands versus store brands, five of which we briefly examine below:

4.1 What are the most important drivers of the premiums?

While several of the above-mentioned drivers have been well documented in isolation (or within a small subset of candidate drivers), we know little about the relative importance of the major classes of drivers. Are the premiums mostly driven by national brand characteristics and actions, and thus largely under the control of national brand manufacturers? Or do retailer characteristics and actions yield most influence on the price, volume and margin premium of national brands over store brands? Alternatively, do (external changes to) consumer characteristics determine the fate of national and store brands in a category? Answering these questions requires a comprehensive study, including the following variables:

(a) Brand manufacturers: prices, quality, innovation, imagery, distribution, promotions, packaging, marketing communication spending, volume versus margin goals.
(b) Category characteristics: category concentration, size, growth, etc.
(c) Retailer characteristics: size, marketing spending, quality and price image, EDLP versus Hi-Lo, country and format type (e.g. grocery store, drug store versus mass merchandisers), store brand portfolio, store brand experience, etc.
(d) Consumer characteristics: quality and price sensitivity, brand loyalty, innovation proneness, product usage occasions and their importance for consumers' self-image (Assael, 1998), hedonic value (Holbrook and Hirschman, 1982), and social expressive or sign value (McCracken, 1986), etc.

4.2 To what extent do store brand investments benefit the investing retailer?

While many retailers appear to believe they reap the full benefits of investments in store brands, recent research has called this into question. First, it appears that most store brand shoppers are 'loyal' to store brands in general, not to the store brands of any specific retailers (Ailawadi et al., 2008). Because store-brand-prone shoppers may not be most profitable for a retailer (Ailawadi and Harlam, 2004), pushing the store brand at the expense of national brands may not be best strategy to increase retailer profitability. Moreover, Szymanowski and Gijsbrechts (2007) find that investments in store brand quality and reputation by one retailer appear to benefit other retailers. Reputation spillovers constitute a pitfall, as they limit the potential of store brands to differentiate retailers. As such, retailers wishing to use store brands as a differentiating strategy need to pursue a quality leadership strategy with their store brands. Such an approach diminishes subsidizing of rival brands or suffering from negative quality perception spillovers from these brands.

4.3 Can manufacturers manage premiums with product line extensions and contractions?

With the growth of their store brand programs, retailers are willing to carry those manufacturer brand assortments that result from successful product innovation and are able to command price and volume premiums. In this context, it has been increasingly important for manufacturers to add SKUs that enhance brand equity while at the same time deleting SKUs that do not enhance brand equity. A recent paper by Pauwels et al. (2007) examines the impact on brand price premium and volume premiums with a focus on manufacturer product assortment decisions. Specifically, they analyze the weekly short-term and long-term effects of SKU additions and deletions on the components of brand equity – brand price premium and brand sales volume premium – over the store brand. From a manufacturer perspective, SKU additions with similar attribute levels as the store brand are found to lower market-based brand equity while SKU additions are especially beneficial in categories with a high store brand share.

4.4 Do store brands provide a reference price for how much a basic product should cost?

The store brand's price could be an important external reference price against which the national brand price is evaluated (Deleersnyder et al., 2007). Many researchers (Ailawadi et al., 2003) have suggested the use of store brands as the comparison brands for national brands. This is important for novices and could shape their price image of the retailer. Despite its managerial relevance, store price image research in the marketing literature

has remained quite scarce, and research is needed to generate guidelines for retailers on how to manage store price image (Lourenço et al., 2007).

4.5 Are multi-tier store brands the holy grail for retailers?

Consultants and retailers alike believe that adding premium store brands is the number one growth priority, but preliminary evidence suggests complex and surprising substitution patterns in the presence of such store brands (Geyskens et al., 2007). Given the growth of multi-tier store brand portfolio strategies, it is increasingly important for retailers to understand whether a three-tier store brand strategy enhances their store brands to make them stronger competitors to manufacturer brands. Will the introduction of a premium store brand versus an economy store brand reinforce the standard store brand's position in the eyes of the consumer, or will it cannibalize the retailer's existing store brand offering? Or will the economy store brand simply steal share from the incumbent standard store brand and possibly even backlash on the image of the retailer's standard store brand line (Kumar and Steenkamp, 2007)? Addressing these questions, Geyskens et al. (2007) show that whereas incumbent store brands have borne the brunt of the negative impact in terms of consumer preferences, the introduction of economy and premium store brands may actually be beneficial for premium and secondary national brands.

Overall, store brands affect the pricing of national brands in complex ways. In this new environment, where retailers have succeeded in building up trusted store brands, manufacturers and retailers need to find 'win–win' situations in order to be successful in the market. In order to make further inroads, retailers will, for example, increasingly need to adopt a portfolio approach to managing their product lines. Manufacturers will be able to recapture their significance to consumers by continuing to innovate and use SKU assortment strategies that enhance brand equity. The findings in this chapter are important because they show the empirical realization of mutual benefits and because they identify marketing strategies that lead to such win–win situations. Ultimately, the nature of the competitive/cooperative interactions between manufacturers and retailers helps determine success versus failure in tomorrow's marketplace.

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13 Trade promotions*

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Abstract

Trade promotions are price incentives given by manufacturers of products and services to their intermediaries such as a dealer, distributor and retailer as part of their overall marketing strategy. In this chapter past research on trade promotion is examined and issues relating to the rationale behind these, the potential impact on the channel partners and managerial aspects of implementation are discussed. Key research issues for researchers working in this area are highlighted.

1. Introduction

In many B2C markets manufacturers distribute their products and services through a set of intermediaries. These are retailers, distributors and brokers. See Figure 13.1. Whether there is only a retailer between the manufacturer and consumer or multiple layers of channel members might depend on the size of the retailer and other factors. Manufacturers use multiple instruments to promote their products to their customers (retailers) and consumers (end users) to stimulate demand and grow. Promotional instruments directed at consumers include advertising, consumer promotions such as coupons, contests, special packages and other incentives. Incentives directed at the trade are trade promotions, category management initiatives such as assistance with planograms, merchandising support, demand forecasts, inventory support etc. Trade promotions are incentives given by a manufacturer of products and services to its supply chain partners, distributors/dealers/retailers, to promote its products to the ultimate end users. Trade promotion spending has been averaging around 14 percent of sales over the last 15 years or so (AC Nielsen Co., 2004). A similar report by AC Nielsen in 2004 states that 53 percent of manufacturers and retailers report 'a measurable increase' in trade promotion spending, while 35 percent and 36 percent of manufacturers and retailers respectively are satisfied with the value they get out of trade promotions. An Accenture report on 'Capturing and sustaining value opportunities in trade promotion' (2001) reports that while advertising, consumer promotion and trade promotion account for 23 percent of sales in 2005, trade promotion alone accounts for 13 percent of sales, quite consistent with the AC Nielsen report. Whether trade promotions are effective in delivering the stated goals for the manufacturers is debatable. The above-cited Accenture report, for example, claims that while CPG (consumer packaged goods) manufacturers spent in excess of $25 billion on trade promotion in 2005, the incremental revenue was only $2–4 billion, suggesting that, at the aggregate, trade promotions lost money for the manufacturers. Citing a Forrester Research report, Inforte Corp. claims in its report that in 2002 manufacturers spent $80 billion on trade promotion with an annual growth rate of 5–8 percent (Inforte

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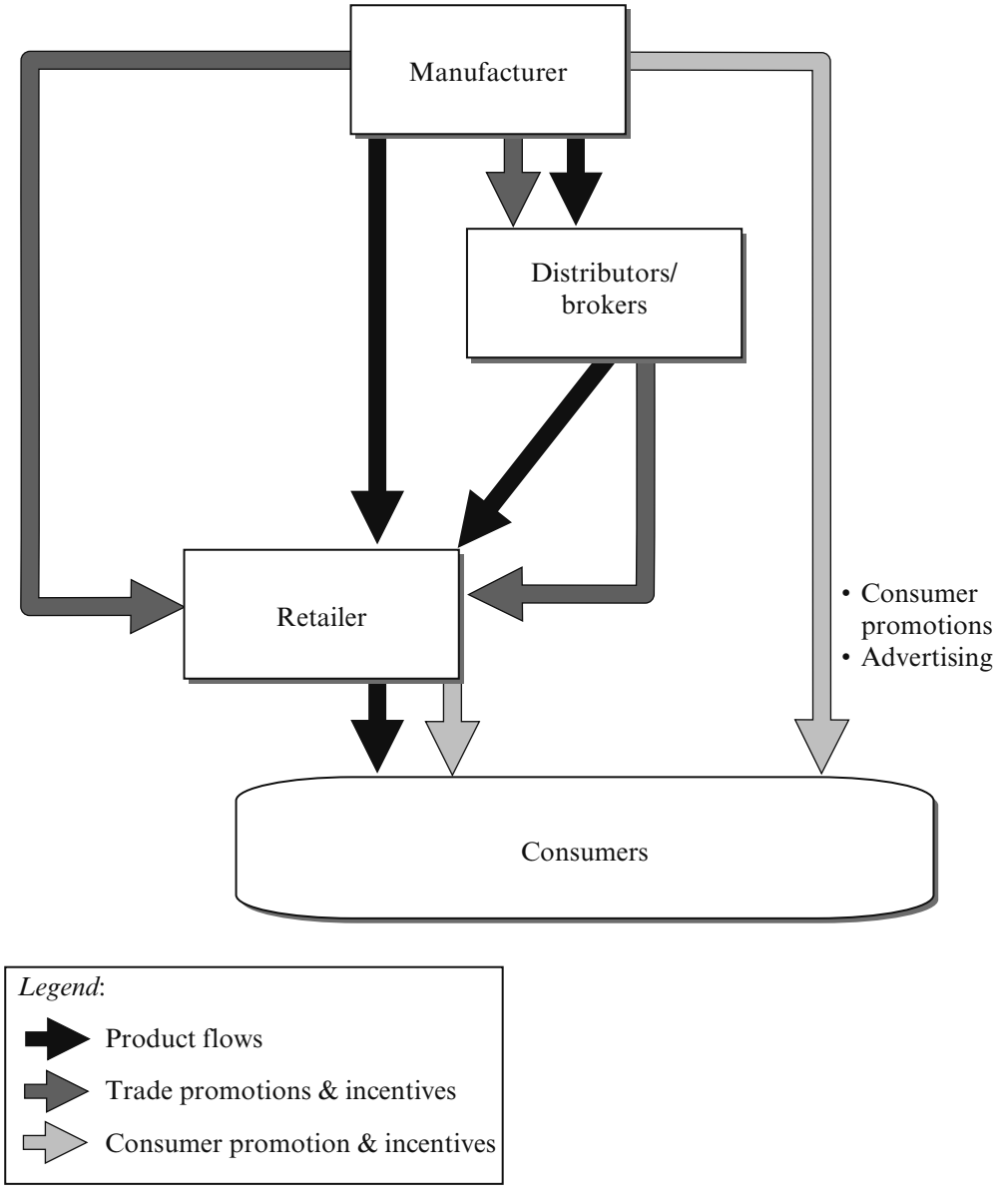

Figure 13.1 Manufacturer–consumer link in a supply chain

Corp., 2005). A recent Booz Allen Hamilton report states that 'manufacturers are so focused in generating additional volume that the overall efficiency of their trade investment is low', and goes on to claim that manufacturers lose a third of the money spent on trade promotions (Booz Allen Hamilton, 2003). This report also states that trade promotion is the second-largest item in the profit and loss account next only to COGS (cost of goods sold). While in nominal terms the money spent has been increasing, as a percentage

of sales, at least in CPG, it has been in a narrow range between 13 and 15 percent. From these industry studies reported in the popular press and research reports by various agencies it seems clear that trade promotion is an important marketing mix variable, CPG manufacturers predominantly use it, these promotions take different forms, and their efficiency in delivering the stated goals of the manufacturers is debatable.

In this chapter I summarize the extant academic literature on trade promotions and identify key research issues relevant to academics and practitioners. The reminder of the chapter is organized as follows. In Section 2, I provide some background on the types and forms of incentives that manufacturers provide to the trade. In Section 3, I examine analytical and empirical literature on retailer behavior relating to such practices and manufacturers' incentives to offer trade promotions. In Section 4, I discuss issues that pertain to the evaluation of the efficacy and profitability of trade promotions. In Section 5, I discuss literature on the role of trade promotion as part of the marketing mix. I conclude the chapter with a discussion of key issues.

2. Types of trade incentives and objectives of trade promotions

If we define trade incentives as broadly any money or allowance provided to the trade, then these incentives take many forms. Blattberg and Neslin (1990) list several different types of trade incentives for durable and non-durable products. Among the main ones are:

1. *Slotting and renewable allowances* These are payments made to the trade for stocking a manufacturer's product, often on a per SKU (stock-keeping unit) per store basis. While stocking fee or allowance is normally associated with new products, renewable allowances are sometimes paid on existing products as well.
2. *Display or feature allowance* Money paid for setting up special displays of a manufacturer's product or advertising the product.
3. *Co-op advertising allowances*, where the manufacturer lets the retailer participate in a manufacturer's advertising or pays part of the cost.
4. *Off-invoice allowance* Here the manufacturer sells a product, as many units as the retailer desires, at a lower price than given on a regular list price. Such a promotion may last anywhere from one to several weeks.
5. *Scanback allowance* Here the manufacturer reimburses the retailer an amount on every unit sold over a specified period. Thus, while off-invoice is a price reduction on every unit bought, scan-back allowance is on every unit sold by the retailer over a specified period.
6. *Free goods* Usually a case free for every n cases bought by the retailer. For all practical purposes this is almost like an off-invoice promotion but forces the retailer to buy n cases before he can get the price reduction.
7. *Volume discounts*, based on the past year's purchases.

These incentives are usually accompanied by certain 'requirements' that retailers have to meet. For example, cigarette manufacturers pay promotion money depending on facings, types of display, in-store advertising etc. (Bloom, 2001). The extent of these promotions varies depending on the type of retail outlet, such as supermarkets, drug stores, mass merchandisers/discounters, convenience stores and warehouse clubs, and type

of categories, such as CPG, cigarettes and drugs. Similarly, slotting allowances would require a minimum level of facings, inventory support and so on. Unfortunately there is very little systematic documentation of these and their trends over time. As stated in the Introduction, the level of these promotions has increased over time. Thus, while there are many types of trade incentives, the term 'trade promotions' as used in marketing refers to per unit reduction in wholesale price, and for most of the remainder of this chapter I review and consider research that focuses on this type of incentive.

2.1 Strategic objectives of trade promotions

There are several objectives of trade promotion. I list the major ones below.

1. *Liquidating excess inventory* When demand and supply are out of sync, a firm may be saddled with excess inventory in the supply chain and needs to get rid of it. Common examples are seasonal items such as snow throwers and lawn mowers, and end-of season model clearances in apparel, certain electronic items and automobiles.
2. *Introducing new product* Trade promotions provide a discount from a reference price to convey to consumers and the trade that the product is sold at an introductory discount. If the retailers in turn choose to pass through some or the entire discount, this could stimulate initial trial.
3. *Stimulate demand* If there are segments of consumers that would react differently to retail promotions, then trade promotions can be an effective tool to reach them.
4. *Competitive response* In response to trade promotions offered by competing manufacturers, a firm may choose to offer trade promotions. Of course this begs the question as to why the other manufacturers offered trade promotions to start with.

2.2 Trade promotion as part of the overall pricing strategy

In marketing their products to the ultimate end users through a set of intermediaries (see Figure 13.1), manufacturers use the entire marketing mix to gain acceptance of their products by the trade and to penetrate the end user market. Conditional on product quality, assortment, flavors or product line, and branding, the marketing mix used to achieve these objectives is price, advertising, and consumer and trade promotions. Thus the role of trade promotions needs to be understood in the larger context of brand competition, supply chain power and brand equity or brand strength. There is clearly a tradeoff between using more of one type of promotion versus another or advertising or a lower price.

In the early 1990s, for example, P&G made a strategic choice to streamline their product offerings by reducing the massive amount of trade and consumer incentives and adopting an EDLP strategy for many of their products. Similarly, recent empirical evidence suggests that slotting allowance, a form of trade incentive offered by firms to gain distribution for new products, has been on the rise. If the result of a trade promotion is to stimulate demand by encouraging retailers to promote the product in turn, a natural question that must be asked and answered is 'Why are these promotions temporary and why not set a low "regular" price rather than periodically providing discounts to the trade?' Thus firms should strategically choose the level of importance and amount of money spent on trade promotion as a part of their overall mix, and not in isolation or as an afterthought. This means that the strategic objectives of trade promotion should be

understood and the allocation to trade promotion should be made in conjunction with the regular price. We revisit this issue in the final section.

3. Retail response to manufacturers' promotions

Before I offer plausible reasons why manufacturers may want to give promotions to the trade, it is instructive to examine how a retailer might respond and the documented evidence in support of this. Almost the entire academic literature considers only price-off promotions, i.e. either off-invoice or scanback promotions, and I shall therefore confine myself to these types of promotion.

When a manufacturer offers a price-off incentive, what would be the response of the retailer in terms of the retail price he charges? By this we mean what is the impact of a trade promotion on the retail price of the promoted product and perhaps even other products in the category? Most retailers are multiproduct retailers. A retailer also competes with other retailers in his trading area. If we assume that retailers want to maximize the total store profit, then a retailer's response to a manufacturer's promotion would depend on a host of factors that include the brand strength of the promoted product, its ability to attract consumers, the available substitutes and complements and the margins on these, the potential action of other retailers etc. From an analytical point of view it is worthwhile to characterize the role of these drivers and reconcile these with the empirical facts. We start with the empirical papers.

3.1 Empirical facts and documented evidence

The empirical literature on retail response has addressed two issues. What is the rate of retail pass-through and what are some factors that affect this? By pass-through we mean the percentage of money that is received from a manufacturer that is passed through to the ultimate consumers, or, more specifically, the change in the retail price due to a change in the wholesale price. Thus 100 percent pass-through means that every penny that is received via a wholesale price reduction is reflected as a penny reduction in the retail price.

Chevalier and Curhan (1976) examined over 990 trade promotions received by a single grocery chain and found that the chain supported only about one-third of the products with any kind of promotional support in the form of a price cut, display or feature advertising. Over 45 percent of the products for which the chain got trade promotions did not receive any retail support. But, conditional on promoting through a price reduction, the average retail pass-through rate was 126 percent. Moreover, the authors found that the sales movement of the brand had a significant impact on the retail support while package size, rank of a product in its category or the amount of money received had no predictable impact. Somewhat contrary to this, Walters (1989), using data from two grocery chains, found that the size of the incentive has a positive effect on the level of retail support. In addition he found that sales volume (consistent with Chevalier and Curhan), compliance requirements (such as manufacturer-paid feature or display support) and price elasticity of the brand affect positively the level of retail support. Armstrong (1991) also documents that across many categories pass-through rates vary, and can be greater than 100 percent.

More recently Besanko et al. (2005) examined own-brand and cross-brand retail pass-through using data from a supermarket chain in 11 categories and 78 products. They estimate a reduced-form model of the following form:

$$P\{i\} = f(c\{i\}, c\{-i\}, \delta) \tag{13.1}$$

where $P\{i\}$ is the retail price of brand i, $c\{i\}$ is the wholesale price of brand i, $c\{-i\}$ is a vector of wholesale prices of all other brands in the category and δ is a vector of exogenous shift variables. They estimate the above model using liner, log linear and a flexible polynomial specification. The estimates of interest are the marginal change in $P\{i\}$ with respect to a small change in $c\{i\}$ and $c\{-i\}$, that is own- and cross-brand pass-through. They estimate (13.1) for each product, using the three specifications mentioned, by pooling data across different price zones of the chain and including shift variables to control for interzone heterogeneity. They report that nearly 70 percent of the estimates of pass-through are significant and positive. This pass-through rate varies significantly across categories with beer and detergent getting larger pass-through than categories such as toothpaste and paper towel. The range is quite large, with average pass-through rate of 22 percent in toothpaste to over 550 percent in beer. The pass-through rate on own brand is on average more than 60 percent in most of the categories they examined. They find the cross-brand pass-through to be positive and negative. They find that market share, and a brand's importance or contribution to the category profit positively influence pass-through. Moreover, a large brand's promotion is less likely to generate cross-brand pass-through on smaller brands than the other way around.

The data used by Besanko et al. come from a chain where the recorded wholesale price is not the actual wholesale price but rather is an 'average acquisition cost' (see Peltzman, 2000) that is based on a weighted average of past prices and past inventory. Thus it is not the strategic choice variable of the manufacturer. This leads to a potential bias towards overstating the pass-through effect and the size of the bias is unknown. Meza and Sudhir (2006) claim that in the presence of forward buying by a retailer, using this acquisition cost measure as a proxy for true wholesale price leads to less of a bias than not using the inventory data at all. McAlister (2005) takes issue with Besanko et al.'s methodology and conclusions. She argues that a typical retailer carrying around 30 000 SKUS will be unable to optimize as the model claims; manufacturers would rationally withhold trade promotion support if they know that their brands' retail prices can fluctuate depending on their competitors' promotions; variability of promotional deals masks the true wholesale prices; measurement errors exist in accounting for promotions etc. Conducting a more detailed analysis of the detergent data Besanko et al. used, McAlister offers further support for the view that the significance of cross-brand promotions is overstated.

Meza and Sudhir (2006) criticize earlier empirical studies for the methodology used to uncover the pass-through rate. Since a typical grocery product category is subjected to seasonal demand shocks, retail prices could be adjusting to these shocks independent of any wholesale price fluctuations and therefore this needs to be accounted for in determining pass-through rates. Starting with a random utility model at the individual level and aggregating to the store-level demand for a brand, they estimate store-level market share equations using the same database as Besanko et al. However, they estimate using only two categories: tuna, which was used by Besanko et al., and beer, which was not used by Besanko et al. By estimating a demand model with data from 94 stores over 400 weeks they infer the pass-through rates and show that loss leaders receive a higher pass-through than other products, and that this rate is lower during periods of high demand.

To summarize, the empirical literature documents the following:

- Not all trade promotions are reflected in retail promotions or pass-through.
- There is considerable variation in this pass-through across brands and across categories.
- The pass-through rates can be more than 100 percent and often, in some categories, substantially more.
- A brand's market share and sales volume affect positively the rate of pass-through.
- There is some evidence that the cross-brand pass-through and a smaller brands trade promotion might lead to pass-through on a larger brand. But more analysis is needed to establish this more convincingly. Similarly, certain categories, due to their importance in attracting store traffic, could potentially receive a higher pass-through.

Thus, while we have evidence on the variability of pass-through, a more systematic analysis of the behavior of wholesale prices and retail prices needs to be conducted to make accurate inferences about the impact of wholesale prices on retail prices. This means that we need econometric models grounded in theory that simultaneously account for the behavior of wholesale and retail prices so that we can make inferences about the impact of the former on the latter. Notwithstanding my admonition, how can these tentative 'facts' be reconciled with optimal behavior of market players? To assess this, we turn to the analytical literature.

3.2 Analytical models of retail response to trade promotions

Tyagi (1999) characterized the optimal response of a single-product monopoly retailer faced with a trade promotion, i.e. reduction in the wholesale price. The retailer is a Stackelberg follower in pricing, and takes the wholesale price as given and sets the retail price. He showed that if the retail demand function is concave or quasi concave, the pass-through rate is <100 percent and if convex, such as a constant elasticity demand function, then the pass-through rate is greater than 100 percent. His paper thus offers support for >100 percent pass-through based purely on the shape of the demand function. Kumar et al. (2001), in their attempt to explain the empirical facts, consider a single manufacturer–retailer dyad selling a single product. The elements of their model are as follows:

- There are two segments of consumers, low valuation and high valuation, that derive net utility of $v - p$ and $\delta^* v - p$ respectively, where v is the intrinsic utility for the single product in the market, p is the price and $\delta > 1$.
- Consumers know the frequency (α) with which manufacturers offer trade promotions, and on observing the retail price at the focal retailer make inference about whether the retailer is being opportunistic (not passing on the trade promotion) or whether the wholesale price is really high and consequently the retail price is at its regular level.
- Based on this, consumers decide to buy from this retailer or choose an outside option, which is to buy from another retailer.

- The manufacturer can use advertising to mitigate the retailer's opportunism by choosing to inform a fraction (φ) of the market about the trade promotion offer.
- The game sequence is as follows. The manufacturer selects φ, the retailer selects the likelihood he would offer a consumer promotion. Consumers observe φ and the retail price and decide whether or not to buy from this retailer.

Kumar et al. show that, in this world, the retailer does not always pass through and is less likely to pass through the greater the level of discount (inconsistent with Walters, 1989), lower the frequency of trade promotions, and lower the manufacturer support through advertising of the promotions (consistent with Walters, 1989).

Lal and Villas-Boas (1998) consider more complex consumer heterogeneity in the presence of retail and manufacturer competition, with each manufacturer selling a single product. There are two manufacturers selling one product each through two retailers and consumers can be in one of nine segments (size): a most price-sensitive segment (S) that buys the cheapest product in the market, two retailer-loyal segments (R) that buy from a single retailer the lowest-priced product, two manufacturer-loyal segments (M) that buy from the cheapest retailer, and four retailer–manufacturer-loyal (that is they are loyal to one retailer and one brand) segments (I). All consumers buy one unit of the product as long as the price is less than the common reservation value r. The game is set as follows:

- Manufacturers set wholesale prices simultaneously to maximize profits.
- Retailers take the wholesale prices as given and set retail prices simultaneously to maximize their profits.
- Consumers decide on the store and brand to buy.

When there is no retailer loyalty ($R = I = 0$), there is no retailer power and retail prices equal wholesale prices, which follows the equilibrium described in Narasimhan (1988). Similarly, when there is no manufacturer loyalty ($M = I = 0$), the manufacturers have no market power, wholesale prices equal marginal cost and now the retail prices track Narasimhan's model. When the market consists of no manufacturer switchers, i.e. $R = S = 0$, all prices are equal to r. If there are no retail switchers, i.e. $M = S = 0$, retail prices equal r and manufacturers randomize as in Narasimhan's model.

In the more general cases Lal and Villas-Boas show that the retail equilibrium can be quite complex depending on the relative magnitudes of the segments, and in some cases, it is possible for the retailer not to promote a brand when that brand's wholesale price is lowered, i.e. under trade promotion. Moreover, in some cases the brand that has the highest wholesale price can have the lowest retail price. An important contribution of this paper is to show when results from prior work such as Narasimhan (1988) will continue to hold and when the equilibrium will be qualitatively different.

Moorthy (2005) extends this literature by considering multiproduct retailers and retail competition. Consider for example two retailers carrying two brands, each with one brand common between the two and the other an exclusive brand that can be interpreted as a private label. Unlike in much of the literature, the demand functions are assumed continuous functions of all prices. In addition to wholesale price changes, the author

considers variety of cost shocks that could lead to a change in retail price. The profit function for retailer i can be written as

$$\Pi^i(\mathbf{P}) = (p_{i1} - w_1 - c_{i1} - c_i - c)\, D^{i1}(\mathbf{P}) + (p_{i2} - c_{i2} - c_i - c)\, D^{i2}(\mathbf{P}) \quad (13.2)$$

where **P** is the vector of all prices

w_1 is the wholesale price of the brand that is common among retailers
c_{i1} and c_{i2} are retailer i's brand-specific marginal costs
c_i is retailer i's non-brand-specific marginal cost such as labor cost
c is a non-brand, non-retailer-specific cost such as excise cost
D^{i1} and D^{i2} are the demand functions for product 1 and 2 respectively at retailer i.

Moorthy examines how, if the retailer maximizes category profits, retail prices will change with respect to wholesale price and the different marginal costs. He shows that the response due to a trade promotion is always positive, leading to a retail promotion. This pass-through would be greater with retail competition and the adoption of category management by the retailers. He also shows that cross-brand effects are ambiguous, i.e. can be both positive and negative, a conclusion supported by Besanko et al.

To summarize, analytical models explain how optimizing retailers' behavior can lead to (i) pass-through of trade promotion, (ii) the pass-through can be greater than 100 percent depending on the shape of the demand function, (iii) in some instances the retailer may not pass through at all, and (iv) cross-brand pass-through can arise but its direction can be positive or negative.

3.3 Manufacturers' incentives to offer trade promotions

At the heart of trade promotions is the question: why do manufacturers offer temporary reduction in wholesale prices? Notice that there are two questions here: (i) why is the incentive tied to the wholesale price as opposed to lump sum payment such as a display support or feature support, and (ii) why are these promotions temporary? The null hypothesis on the second question is: why not offer a permanent reduction in wholesale price? Clearly, if there are demand (seasonality, mismatch between forecast and realization of demand etc.) shocks or supply shocks (crop prices, labor costs) we should observe a temporary fluctuation on wholesale prices. But most trade promotions cannot be dismissed as arising out of these random shocks. There must be consumer, supply chain and competitive factors that lead to such promotions. This second question takes on added importance when we factor in the direct and indirect costs of trade promotion (see Buzzell et al., 1990). One of these costs is the opportunity cost or foregone profit if retailers forward buy on trade promotions. If retailers buy more than what they require to meet the compliance requirements and use the additional quantity to sell the product at its normal regular price, this represents a loss or cost of that trade promotion. We examine the answers provided by analytical models of consumers, intermediaries and manufacturers.

Jeuland and Narasimhan (1985) offered a model of two parties – a monopoly firm and consumers – to explain the occurrence of promotions. There are two segments of consumers who differ in their preferences and inventory costs. The demand for a product at the segment level is given by

$$Q_i = \alpha_i - \beta * P \tag{13.3}$$

where Q_i is the demand for segment i and P is the retail price, α_i is the segment specific parameter and β is the price sensitivity parameter.

The authors assume that the segment with higher α has a higher holding cost for inventorying this product, only buys for current consumption and does not forward-buy. The consumers with lower α, when faced with a retail promotion, respond by increasing their consumption and forward buying the product when it is on sale. They show that the optimal strategy for the monopolist is to conduct periodic sales and solve for the frequency and depth of promotion. The contribution of this paper is to show that consumer heterogeneity in inventory costs and demand elasticity, and correlation between these, can drive periodic promotion by a manufacturer. While they didn't identify the consumers as retailers, they could apply their model to trade promotions as well. As long as there are enough customers able to expand their demand and forward-buy, it is optimal for the firm to offer trade promotions. Lal (1990) offers a model with two competing manufacturers marketing one brand each through a retailer who offers a store brand. He shows that in an infinitely repeated game the manufacturers take turns to offer a trade deal to the retailer. Thus in a non-cooperative game the manufacturers collude to limit the encroachment by the store brand into their franchises. Lal et al. (1996) consider a model of two competing manufacturers selling one product each through a common retailer. The manufacturer incurs a selling cost of promotion and the retailer, if he accepts the promotion, incurs a fixed cost. The retailer can buy the product either at the regular price or at the promoted price and can forward-buy products for future use. The demand model has features similar to models without a retailer (see Narasimhan, 1988). As in earlier models, manufacturers use a randomized strategy in offering discounts to induce the retailer to inventory their products. An important contribution of this paper is to show that even when the retailer forward-buys, manufacturers find it profitable to offer a trade deal. The reason is that holding inventory leads to less intense price competition since smaller deals are less attractive to the retailer when he has inventory and larger deals become unprofitable to the manufacturers. So the manufacturers compete over a narrower range of trade deals, which means that the probability of beating your opponent (i.e. the retailer will accept the deal) is lower and therefore the manufacturers are less aggressive.

A paper that models manufacturer promotion not as a wholesale price reduction but as a lump sum transfer is by Kim and Staelin (1999), who consider a model of two manufacturers selling one product each and two retailers who sell two products each. Trade promotion is captured through a lump sum allowance that a manufacturer provides a retailer. Each retailer selects the retail prices and a common pass-through rate for the two brands. The 'pass-through rate' is the proportion of this allowance spent on merchandising activity that affects demand positively. Retail demand for brand i at the retailer is given by the following:

> Demand for brand 1 at store 1 = f (prices of all brands at store 1, pass-through rate at store 1*difference in the promotional allowance of brand 1 in store 1, difference in promotional allowances across stores, pass-through rate at store1*promotional allowance at store1)

Thus the demand function captures the effect of prices, own- and cross-brand pass-through, store switching and category expansion. The game proceeds as follows. Each

manufacturer simultaneously chooses wholesale price and promotional allowance for his brand, anticipating the actions of the retailers. In the second stage, retailers simultaneously choose retail prices and pass-through rates. Two broad conclusions emerge from this paper. First, it offers analytical support to the evidence and argument made earlier by Messinger and Narasimhan (1995) that even when manufacturers provide greater concessions to the retailers, because of retail competition these concessions are passed along aggressively by the retailers. Second, the authors show that even though retailers pass through less than they receive, manufacturers provide the side payments to the retailers.

A different rationale for the existence of trade promotions and allowances is provided by the research stream that examines the channel relationship when the retailer not only distributes manufacturers' products but also markets a store brand. Narasimhan and Wilcox (1998) consider a manufacturer–retailer channel where the retailer is able to procure a private label in a competitive market. There are two segments of consumers, one loyal to the national brand and another that is composed of national brand–private label switchers. All consumers buy one unit of either the national brand or the private label as long as the price of that product is less than $\$r$, the reservation price. A randomly chosen consumer in the switching has a preference for the national brand but will buy the private label if the retail price of the private label is $\$l$ less than the national brand. They assume that l is distributed $U(0, L)$. The manufacturer sets his wholesale price anticipating retailer's pricing behavior in relation not only to the national brand but also to the private label. They compute the equilibrium prices with and without private labels. They show that the retail margin on the national brand is positively related to the size of the switching segment and is negatively related to the heterogeneity of the switching segment. The first result is obvious. The second result arises due to the fact that as the heterogeneity in the switching segment increases, it is more costly for the retailer to attract the same proportion of switchers away from the national brand, which leads to lower concession from the manufacturer. The authors thus show that not only does a private label have a direct effect in terms of attracting more customers in the market; it also has a strategic effect of eliciting better wholesale price concessions from the manufacturer. They offer empirical support to their predictions.

To summarize, we have the following predictions from the analytical models:

- Retailers in general will pass through manufacturers' incentives. Greater than 100 percent pass-through is predicated upon the shape of the demand curve.
- Ignoring menu costs and adjustment costs of changing prices, cross-brand pass-through is likely to occur.
- Even if retailers forward-buy, in a competitive world we should see trade promotions.
- Retail competition forces retailers to pass through more than they would normally have passed through based on demand and cost curves.
- Trade promotions or concessions from manufacturers can arise when retailers market store brands or private labels.

4. Profitability and efficacy of trade promotions

In this section we discuss two key managerial issues: (i) how should one evaluate the profitability of trade promotions and (ii) how can one make trade promotions more effective in achieving stated objectives?

4.1 Evaluating the profitability of trade promotions

At first glance this seems a very simple task. Compare the profits with and without promotion and if the latter are greater than the former, declare victory because the promotion is profitable. But closer examination reveals that it is not simple: evaluation of promotion is fraught with many measurement and data problems. To understand the difficulties, let us think about what happens when a promotion occurs by focusing on off-invoice promotion. If retailers anticipate that such promotions are temporary, they are likely to be strategic and engage in forward-buying. Likewise there is a large body evidence that consumers, when faced with retail promotions, forward-buy; more recent evidence (see, e.g., Van Heerde et al., 2003; Chan et al., 2008) seems to suggest that such stockpiling behavior accounts for a major portion of the sales spike. The amount that is forward bought is potentially an opportunity loss since these units could have been sold at the regular price at some point later in time. Of course not all of it is a loss since there is no guarantee that the retailer would have bought the same amount in future. Moreover, wholesale demand and retail demand of a product are subject to random shocks and competitive actions. Given all this, determining incremental sales due to a promotion is a complicated task. If consumers and retailers act strategically, examining shipments data in a 'before versus after' promotion analysis will be misleading. Next is the question of identifying direct and indirect costs of promotion. What are the direct costs of running a trade promotion? What about the indirect or opportunity costs of accumulating higher inventory in preparation for a promotion etc? Thus, even if one can estimate the incremental sales, identifying the direct and indirect costs to evaluate profitability of promotions is daunting. Two papers tried to tackle the profitability of promotion using sales and shipment data.

Blattberg and Levin (1987) use a three-equation model and an accounting identity to predict shipments and consumer sales as below:

$$\begin{aligned}
\text{Shipments } \{t\} &= f1\ (\text{inventory } \{t-1\}, \text{trade promotions, other factors}) \\
\text{Retail promotions } \{t\} &= f2(\text{trade promotions } \{t\}, \text{trade promotions } \{t-1\}, \\
&\quad \text{inventories } \{t-1\}) \\
\text{Consumer sales } \{t\} &= g\ (\text{trade promotions } \{t\}, \text{retail promotions } \{t-1\}, \\
&\quad \text{other factors } \{t\}, \text{other factors } \{t-1\}) \\
\text{Inventories } \{t\} &= h\ (\text{inventories } \{t-1\}, \text{shipments } \{t\}, \text{consumer sales } \{t\})
\end{aligned}$$

They estimate the model using data from ten products and three markets. Using the estimates, one can simulate what will happen when a trade promotion is offered to shipments and retail sales. This model, by being theoretically sound in that it relies on a process model of the flow of goods and money in the system, gives confidence as to face validity. While this is a good beginning, note that they were not able to estimate separately, due to data problems, the second equation above to uncover the factors that drive retail promotions. Moreover, there was no attempt to explicitly control for or model within-category competitive effects or interstore competition. Finally, the consumer sales model can be enriched to include drivers under the control of the retailers such as feature and display support etc.

Abrahim and Lodish (1987) develop an expert system to evaluate the impact of promotion. Their focus is on identifying baseline sales, those that would result in the absence of promotional effects. They define sales at time t as

$$S(t) = T(t) * SI(t) * X(t) \ (b(t) + p(t) + e(t))$$

where T, SI, X are trend, seasonal and 'exception' indices, b, p are the base-level sales and promotional bump after removing trend, seasonality and 'exceptions', and finally e is an error term. Through data analysis and judgment the baseline sales is estimated and, using that, the incremental sales and profitability of any promotion can be estimated. Unlike the Blattberg and Levin model, this model is purely data driven and the statistical property of the baseline sales is not known. Further, the procedure for identifying exceptions seems not to follow from any structure but rather depend on the analyst's judgment. For example, the authors report that category-level and competitive effects are captured by the exception index but it is not made clear how; nor is the robustness of this index measured.

To summarize, there have been some attempts to model the profitability of trade promotions. Largely due to the type of data available and the cost of conducting this exercise, we have not seen more of this type of research but it remains an important area.

4.2 Drivers of effective trade promotions

What are the drivers that improve the effectiveness of trade promotions? How can we use these drivers to optimize the timing and characteristics of promotional offers? To answer the first question, we should develop metrics for effectiveness. Is it just profitability, or are there other measures that we should examine? Hardy (1986) explored this issue through a survey of managers from a sample of 27 Canadian packaged good companies on 103 trade promotions. Each manager was asked to complete the survey instrument for one successful and one unsuccessful promotion. Using these data, Hardy examines through a multiple regression model the drivers for the following four dependent variables: short-term volume, long-term market share, build-up of trade inventories and increased consumer trial. He found that trade support had a predictable impact on all the four metrics. The level of incentives affected positively the short- and long-term share goals while competitive promotion affected negatively the build-up of inventories, with the trade, of the focal brand. These results are intuitive. Blattberg and Neslin (1990), based on a study by Curhan and Kopp (1986), identify the following four factors as influencers on the level of support the retailers would provide:

1. Economic structure of promotions such as amount of discount, terms, requirements and restrictions.
2. Item importance, including volume, category size and competitive retail activity.
3. Manufacturer's reputation.
4. Promotional elasticity.

Murry and Heide (1998) consider the issue of retailer participation and compliance with manufacturer-initiated promotions such as POP programs. They theorize that both interpersonal relationship and incentives matter in retailers' decisions. They designed a

conjoint study that included four factors (two levels each) to capture both organizational and incentive drivers. The study was administered using a full factorial design to liquor and grocery store managers. They found that incentive factors are more important in the decisions of the retailers, and that strength of interpersonal relationship does not diminish this importance.

Which type of trade promotions would be best and what are the drivers? This is somewhat of an underresearched area. Given the structure of these promotional incentives, it is not surprising that manufacturers tend to favor performance-based promotions such as scan-backs while the retailers favor straight off-invoice promotions. Drèze and Bell (2003) show analytically that if the terms of the deals are identical, the above result is valid, but a manufacturer can redesign the scan-back promotion to leave the retailer no worse off while improving his profitability. This is because under scan-back there is no excess ordering and retail price is lowered, resulting in higher retail sales. In their model there is no manufacturer or retail competition, so it is not clear how these added institutional details would change the result.

5. Trade promotion as part of the marketing mix

As any marketing student knows, firms have multiple instruments to stimulate demand and to respond to competitive and channel initiatives. So where does trade promotion fit as part of the overall marketing strategy? How should managers address the problem of budget allocation? I explore these issues in this section.

Narasimhan (1989) explores the factors that are perceived to be important in deciding on consumer and trade promotions. He conducted a survey of brand managers to assess this. He identified three factors that drive the importance attached to trade promotions. These are goal oriented (achieving sales targets, introducing new products, motivating sales force), defensive (maintaining shelf space, meeting competition), and penetration (increasing usage rate and getting more retailer push). The factors for consumer promotion were similar except that there were two goal factors, one short and one long term. He found that the managers' beliefs about the importance of these factors were correlated with category and brand variables such as category, volume, growth rate, shelf life, purchase frequency, market share, rank etc. Finally, he finds that the decision to allocate money between trade and consumer promotions is based not only on category and brand variables but also on the perceived importance of the factors.

Neslin et al. (1995) consider a market consisting of a single manufacturer–retailer dyad and consumers. The manufacturer can advertise the product to consumers and trade-promote to its retailers. Advertising affects retail sales through the pull effect and retail promotion also affects retail sales. The manufacturer is assumed to maximize its net profit over a year by deciding on the optimal allocation between advertising and trade promotions. Unlike the standard analytical models, they do not use a game-theoretic set-up. The amount to be ordered by the retailers, the intensity of promotion at retail level etc., do not come from maximizing behavior by the retailer but rather are written down as exogenous decisions. A demand equation describes the total sales at the retail outlet. They use numerical optimization methods to arrive at an optimal policy for the manufacturer. In the base case, for example, they show that periodic trade promotions and constant advertising expenditures except in the period before a trade promotion is an optimal strategy. While this kind of exercise incorporates a level of richness that is

not found in standard analytical models, the non-strategic behavior of retailers and consumers is a limitation of such an exercise.

Gomez et al. (2007) evaluate the drivers behind the allocation of the trade promotion budget and its components. They hypothesize that the amount of money allocated to trade promotion increases is positively (negatively) correlated with the size of retailer and the brand power of retailer (size of manufacturer, brand strength) while the effect of private label penetration is ambiguous. Similarly, allocation of money between off-invoice and performance-based scan-backs is also driven by these factors. Using survey data from 36 supermarkets in the USA, they test their hypotheses and find support. It is interesting and somewhat intuitive that they find that, with greater retailer size, positioning and power through private label, retailers are able to elicit better concessions from the manufacturer through off-invoice promotions, a point made earlier by Narasimhan and Wilcox (1998).

Gerstner and Hess (1991, 1995) consider the dual role of trade promotions and consumer promotions through coupons or rebates. They consider a manufacturer–retailer dyad with no competition at either level. Consumers are of two types, H and L. The H type has a higher reservation price than the L type. All consumers desire at most one unit of the product as long as the price is less than their reservation price. The manufacturer distributes the product through a retailer and decides on the wholesale price first and, conditional on this, the retailer decides his retail price. As long as the L-type segment size is below a critical level, the manufacturer's optimal strategy is to cater only to the H type. But as the L type grows it is optimal for the manufacturer and for the channel as a whole to sell to both types. But in the standard Stackleberg leader–follower game, if the manufacturer lowers the wholesale price, the retailer has every incentive not to pass along the lowered price to attract the L type due to the standard double marginalization problem. Gerstner and Hess show how the use of pull promotions through rebate or coupon can coordinate the channel. They go on to discuss the effect of coupons and what happens if perfect targeting of low-value consumers is not possible. This paper doesn't capture the essence of trade promotions, which are temporary reductions in wholesale price. These papers offer insights into when a wholesale price reduction is necessary and how other marketing mix variables play a role in enhancing the effectiveness of such a policy. These papers make two interesting points. Consumer promotions in conjunction with trade promotion can coordinate the channel. Pull promotions, in addition to any discriminatory or segmentation effect among end users, can serve an added role in the presence of an intermediary.

Agrawal (1996) considers the effect of brand loyalty on advertising and trade promotion. He constructs a theoretical model that captures two competing manufacturers distributing one brand each and a common retailer that distributes both brands. Consumers desire at most one unit of either product as long as the retail price is less than $\$r$. There are two segments of consumers each loyal to one of the two brands, but each will switch to the other brand if the price of the other brand is lower than a threshold relative to its favorite brand. The retail demand for brand i ($i = 1, 2; j = 3 - i$) can be written as

$$D_i(p_i, p_j) = \begin{cases} 1 & \text{if} \quad p_i < p_j - l_j \\ M_i & \text{if} \quad p_i - l_i \leq p_j \leq p_i + l_j \\ 0 & \text{if} \quad p_j < p_i - l_i \end{cases} \tag{13.4}$$

where p_i and p_j are retail prices, and l_i and l_j represent the threshold the competing brand has to overcome. A firm's own advertising expenditure raises, at a diminishing rate, the threshold the other firm has to overcome but competitive advertising lowers this threshold. So firm *i*'s advertising raises l_i while firm *j*'s advertising lowers l_i and vice versa. The author assumes that the thresholds for two brands are sufficiently different so that the brand with a larger *l* is called the stronger brand and the other the weaker brand. The game proceeds in four stages. In stage one, the two manufacturers simultaneously decide on their respective advertising levels. In stage two they simultaneously set wholesale prices, in stage three the retailer sets the retail prices for the two brands and in stage four consumers observe all the prices and make their choices. He finds that the retailer, similar to Narasimhan's results, promotes the stronger brand more frequently than the weaker brand. Turning to the manufacturer, he finds that there are several equilibria, depending on the marginal cost of advertising, where the stronger brand does not advertise but the weaker brand advertises and the promotional strategy is one of the following:

(a) Neither manufacturer promotes.
(b) Both promote and the weaker brand spends less.
(c) Both promote and the weaker brand spends more.

On pass-through of trade promotions the author finds that the stronger brand enjoys greater pass-through in terms of frequency but not on the size of the discount. Some of these results, especially on the pass-through, seem to be inconsistent with the empirical evidence cited earlier. Using scanner panel data, he examines some of the predictions from his model. To test these predictions he first estimates the size and strength of loyalty for each of 54 brands in seven different categories. Using linear regression he estimates the following three modes at the brand level:

$$\text{Advertising expenditure} = \alpha_0 + \alpha_1 \times \text{loyalty} + \alpha_2 \times \text{size} + \text{category dummies} + \varepsilon_1$$

$$\text{Average retail discount} = \beta_0 + \beta_1 \times \text{loyalty} + \beta_2 \times \text{advertising expenditure} + \text{category dummies} + \varepsilon_2$$

$$\text{Frequency of retail promotions} = \gamma_0 + \gamma_1 \times \text{loyalty} + \gamma_2 \times \text{advertising expenditure} + \text{category dummies} + \varepsilon_3$$

Consistent with his theoretical predictions, he finds that high loyalty leads to lower advertising expenditures, lower retail discount and greater frequency of retail promotions, and loyal segment size is positively related to the manufacturer's advertising expenditure. The contribution of this paper is in considering trade promotions as part of the overall mix in conjunction with advertising and promotions at both the wholesale and retail level.

6. Discussion

In this chapter I discuss several research streams examining the role of trade promotions, the incentives of trading partners in offering and accepting these, the drivers of the

efficacy of trade promotions, evaluating the profitability of trade promotions and how trade promotions may interact with other marketing variables.

Manufacturers, especially CPG manufacturers, have been allocating a greater share of the promotional budget to trade promotions over time. We are also seeing a shift in the allocation among the types of promotions, partly driven by improvements in IT that have lead to better data capture, analysis and monitoring.

Existing research has evolved along the following streams:

- Documenting retailer acceptance and pass-through rates.
- Empirically identifying the drivers of retailer acceptance.
- Analytical models exploring the rationale behind trade promotions in monopoly and competitive contexts.
- Analytical models characterizing the impact of promotions on retailers and their propensity to accept these.
- Models evaluating profitability.
- Understanding the drivers to improve the efficacy and impact of trade promotion.
- Role of trade promotion as part of the marketing mix.

Several conclusions emerge from the extant literature:

- Retailers are selective in passing the money they receive from the manufacturers to the consumers. Surprisingly, several instances have been documented where the retailers pass through more than they receive.
- A brand's strength and its ability to pull sales or increase store traffic (Lal and Narasimhan, 1996), item importance, size and structure of incentives are key predictors of retailer compliance.
- Retail competition increases the pass-through rate.
- Trade promotions can arise even if retailers forward-buy.
- The presence of store brands or private labels acts as an important driver for the manufacturers to offer concessions to trade, often in the form of trade promotions.
- Cross-brand pass-through can occur, although the empirical evidence seems to be somewhat scant or mixed.

Based on this, I expect future research to continue to build on this important topic along the following lines:

- A broader assessment of the empirical regularities across many categories and markets such as in international markets.
- Exploring in greater depth the efficacy and profitability of trade promotions by explicitly modeling retailer characteristics such as size, market share, reputation etc. in the empirical models.
- Extending and checking for robustness of the findings in non-grocery markets such as apparel, electronic goods, toys etc. Some studies have looked at trade promotions in durable goods (Bruce et al., 2005) and dealer promotions in automobiles (Busse et al., 2006). More work along these dimensions would help us to understand

and establish robust drivers for the incidence, acceptance and pass-through of these trade promotions.

- Examining analytically and empirically the promotion incentives, acceptance and performance when there are multiple channels such as brick-and-mortar and online channels.
- Examining the strategic role of trade promotions as part of the overall pricing strategy. How exactly do or should firms design trade incentives and an overall pricing strategy including a regular list price?

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14 Competitive targeted pricing: perspectives from theoretical research*

Z. John Zhang

Abstract
With an unprecedented capability to store and process consumer information, firms today can tailor their pricing to individual consumers based on consumer preferences and past buying behaviors. In this chapter, we discuss this nascent practice of targeted pricing from a theoretical perspective. We focus on three main questions that are relevant to assessing the future of this practice. First, is targeted pricing beneficial to practicing firms? Second, if a firm decides to embrace targeted pricing, what should be its targeting strategy in terms of whom to target and with what incentives? Third, is targeted pricing beneficial to the society as a whole? We draw on the existing literature on targeted pricing to offer some preliminary answers to these questions.

1. Introduction

Targeted pricing, as the term is commonly used by practitioners, refers to the practice where a firm tailors its prices of a product to individual customers based on some discernible differences in their preferences, willingness to pay, buying behaviors, etc. For instance, when selling magazines, a publisher may decide to offer a discount to a new subscriber, but withhold the same discount from someone who has been a loyal subscriber for years. In the famous battle for market share between AT&T and MCI in the early 1990s, AT&T successfully persuaded many MCI customers to switch carriers by offering them personalized checks in the amounts of $25 to $100 depending on each consumer's long-distance calling history and experience with AT&T (Turco, 1993). Today, many industries adopt some form of targeted pricing when they have actionable customer information, and such practices are also variably called 'one-to-one pricing', 'personalized pricing', 'tailored pricing', and sometimes 'dynamic pricing'.

On the surface, targeted pricing is nothing new and merely a form of price discrimination. The textbook definitions for different forms of price discrimination we use today came from the English economist Arthur C. Pigou (1877–1959). In his book *Economics of Welfare*, originally published in 1920, Pigou articulated three forms of price discrimination that a monopolist could implement. To use Pigou's words,

> A first degree would involve the charge of a different price against all the different units of commodity, in such wise that the price exacted for each was equal to the demand price for it, and no consumers' surplus was left to the buyers. A second degree would obtain if a monopolist were able to make n separate prices, in such wise that all units with a demand price greater than x were sold at a price x, all with a demand price less than x and greater than y at a price y, and so on. A third degree would obtain if the monopolist were able to distinguish among his customers n different groups, separated from one another more or less by some practicable mark, and could charge a separate monopoly price to the members of each group. (Pigou, 1929, p. 278)

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However, targeted pricing as practiced in industries today frequently does not fit any of these different forms of price discrimination. For instance, when amazon.com targets its loyal customers with a high price for a book, while charging a new, occasional purchaser a low price for the same, it implements a pricing scheme that cuts across all three forms of price discrimination and, arguably, goes beyond what has been understood to be the standard practices of price discrimination. First, amazon.com's pricing scheme is based primarily on past buying behaviors, rather than on any invariable 'practicable mark' such as gender, age and other demographics. Therefore this practice of targeted pricing is not exactly the third degree of price discrimination where customers with the same characteristics, say being students or senior citizens, are charged the same price. Second, it is not exactly the second degree of price discrimination, either, as both loyal and occasional purchasers are buying the same amount. In addition, it is amazon.com that is assigning a price to individual customers, and customers do not have a chance to self-select in terms of what they end up paying. Finally, this pricing practice is almost certainly not first-degree price discrimination, as the pricing scheme does not tap into variations in willingness to pay that must exist among loyal as well as among occasional customers.

It is perhaps not surprising that a classification scheme developed nearly a century ago can no longer encompass an ever-increasing number of different schemes of price discrimination concocted today by increasingly sophisticated practitioners. In the area of price discrimination, two market forces drive today's practitioners to become ever more inventive. First, the availability of new information technologies and sophisticated database analytics, and the widespread use of Internet transactions allow firms to gather and process detailed customer information on a large scale and in a timely and cost-effective manner. Consequently, firms are having ever-sharper pictures of individual customers so that they can move away from a labor-intensive targeting approach (Desai and Purohit, 2004) and go beyond static, obvious variables such as demographics and purchasing quantities in designing their price discrimination schemes. They can look into consumer preferences, loyalties and other psychographics, as well as geographic and other discernible and quantifiable differences among customers. Second, as the marketplace is becoming increasingly competitive, firms need to tune their pricing schemes constantly to stay ahead of competition when searching and capturing the last pockets of profitability in the marketplace.[1]

The proliferation of targeted pricing practices challenges not only the standard taxonomy of price discrimination, but also much of the conventional wisdom about price discrimination. One such piece of conventional wisdom is that price discrimination should always benefit the practicing firm whether it implements first-, second- or third-degree price discrimination. After all, a firm, by being a monopoly, has the choice not to implement any price discrimination. However, in today's market environment, this logic is no longer valid, and certainly not in the industries where we frequently observe targeted pricing. For example, in the case of AT&T mentioned above, competition is a driving force behind its practice of targeted pricing. Indeed, AT&T's primary targets for its switching checks were MCI's customers. Armed with customer usage information in

[1] Of course, even with conventional price discrimination schemes, competition intensity in a market plays an important role, as shown in Desai (2001).

addition to customer addresses and demographics, AT&T could identify the switchable customers who were served by MCI and gauge the strength of their preferences for MCI to determine the right incentives required to induce them to switch. In this case, price discrimination was implemented based on consumer relative preferences. In addition, targeted pricing did not and could not take place in an insulated market where AT&T could ignore any competitive reactions. As a matter of fact, MCI implemented its own targeted pricing campaign to switch AT&T's customers, too. As a result of competitive targeted pricing, millions of customers switched (perhaps multiple times) between the two firms as they cashed the switching checks received from both firms.

In this new reality of price discrimination, three fundamental questions arise that are of interest to practitioners and marketing scholars alike. First, can firms benefit from targeted pricing in oligopolistic markets? Many practitioners and experts may be tempted to offer a quick 'yes'. However, the answer is not that obvious, considering the complexity involved in implementing targeted pricing in terms of costs, competitive reactions and consumer responses. Yet the answer to this question gives us a perspective to guide the practice of targeted pricing and to assess its future. For instance, if firms become worse off because of targeted pricing, they may not have much incentive to invest in their targeting capability or they may want to seek ways to restrain targeted pricing in their industry. The answer to this question also offers some strategic prescriptions as to whether a firm should adopt targeted pricing and how it should prepare itself for such a future.

Second, if a firm decides to implement targeted pricing, what should be its targeting strategy? In other words, if a firm can identify consumers and charge different prices to different consumers, how should it deploy its capabilities? More concretely, should the firm target its competitor's customers with a discount, its own customers, or both? Our answer to this question can help us to understand the current practice of targeted pricing and offer some strategic guidance to practitioners.

Third, does targeted pricing improve social welfare? Marketers need to pay attention to this question because welfare implications do have regulatory implications, and our answer to this question may affect the legal environment in which targeted pricing is conducted.

In this chapter, we take a brief tour of the recent literature on targeted pricing to see how it answers those three questions. Before we start on that tour, three points are worth noting. First, targeted pricing is a nascent practice. Few data are available that can help us to address those three questions. For that reason, empirical research on targeted pricing mostly focuses on how a firm can or should implement targeted pricing given that it has a certain kind of customer information (Rossi and Allenby, 1993; Rossi et al., 1996; Dong et al., 2006; and Zhang and Wedel, 2007). Theoretical research, in contrast, is uniquely suited for addressing all three questions in a competitive context. Therefore, in this chapter, we focus exclusively on the theoretical literature on targeted pricing.

Second, targeted pricing is an evolving practice, and new ways to implement targeted pricing emerge all the time. Therefore it is infeasible and perhaps even unwise to try to catalog all of the existent practices. The theoretical literature on targeted pricing so far mostly focuses on preference-based and behavior-based targeted pricing and we shall do the same in this chapter. Third, most of the theoretical studies on targeted pricing are fairly complex technically. Such technical complexity has sometimes rendered the literature inaccessible to a broad audience. Therefore, in our opinion it is desirable to discuss the messages of the literature without being unduly encumbered by technicalities.

Towards that objective, we shall use simplified models instead of the original models, whenever possible, to illustrate the basic economics behind the main conclusions of this literature. In what follows, we take up each of the three questions in turn.

2. Would firms benefit from targeted pricing?

The simple answer to this question is 'it depends'! That is, of course, the easy part of the answer. The difficult part is to figure out what it depends on. Many researchers, such as Thisse and Vives (1988), Shaffer and Zhang (1995), Bester and Petrakis (1996), Chen (1997), Fudenberg and Tirole (2000), and Taylor (2003), have investigated this question with different models. We can use a simple model to capture the gist of their arguments.

In any market where targeted pricing is implemented, consumers must be heterogeneous in their preferences and firms must be selling a differentiated product. We can use the standard Hotelling (1929) model to capture both market conditions. Concretely, consider two firms located respectively at 0 and 1 of a unit Hotelling line and set their prices independently. For simplicity, we assume away all production costs. Consumers in the market are uniformly distributed along the unit line and we normalize the number of consumers to one, so we do not need to carry a constant around in our computations. To follow convention, we further assume that each consumer in the market makes at most only a single unit purchase if such a purchase generates positive surplus.

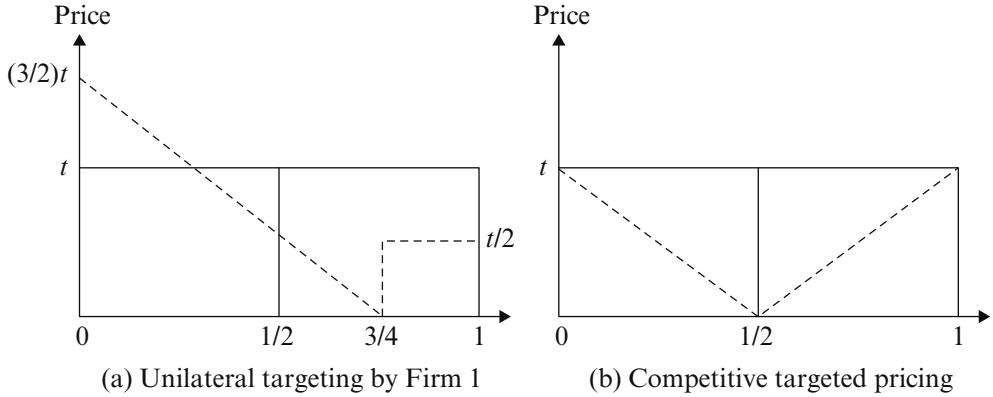
Before a consumer makes a purchase, she will compare the surplus she would get from Firm 1 with that from Firm 2, and choose the firm that provides the most surplus. To make the choice decision more concrete, let V stand for the reservation price that consumers are willing to pay for their 'ideal' product and let t denote the unit transportation cost that a consumer must incur to purchase a non-ideal product. Then, for a consumer located at $x \in [0, 1]$, if she purchases from Firm 1 at the price p_1, the surplus she obtains is $V - p_1 - tx$. If she purchases from Firm 2 at the price p_2, her surplus is $V - p_2 - t(1 - x)$. Thus, depending on the location x, even if both firms charge the same price to a consumer, the consumer will have a definite preference in terms of where she prefers to make the purchase – she will purchase the product that is closer to her ideal product. This preference heterogeneity gives rise to the possibility of using targeted pricing to compete for customers.

To isolate the effect of targeted pricing, let us first establish the benchmark of uniform pricing where each firm can only charge one price to all consumers. In this case, we can easily identify the location of marginal consumers $\tilde{x}$ such that to the left of $\tilde{x}$, all consumers purchase from Firm 1 and, to the right, all consumers purchase from Firm 2. From $V - p_1 - t\tilde{x} = V - p_2 - t(1 - \tilde{x})$, we have

$$\tilde{x} = \frac{p_2 - p_1 + t}{2t} \tag{14.1}$$

Then it is easy to write down each firm's payoff function and they are, respectively, $\pi_1 = p_1\tilde{x}$ and $\pi_2 = p_2(1 - \tilde{x})$. As each firm sets its price to maximize its payoffs, we can derive the equilibrium prices and profits from the first-order conditions and they are, respectively, $p_1 = p_2 = t$ and $\pi_1 = \pi_2 = t/2$. The equilibrium is illustrated in Figure 14.1.

In this equilibrium of uniform pricing, the two competing firms share the market equally, i.e. $\tilde{x} = \frac{1}{2}$. A firm has no incentive to price more aggressively to gain a larger market share in this case because by cutting its price to lure marginal consumers away from the competition, the firm also cuts its price to all consumers who would have purchased from the



Note: The benchmark case of uniform pricing is illustrated with solid lines in both cases.

Figure 14.1 Equilibrium prices and market share

firm without the price cut. In other words, without the flexibility of charging different customers at different locations a different price, a firm must leave more money on the table for those non-marginal customers in order to generate more incremental sales. However, targeted pricing gets a firm out of that bind and gives it the needed flexibility.

To see this, suppose that Firm 1 suddenly gains the capability of implementing targeted pricing in the sense that it can set location-specific prices $p_1(x)$ for all $x \in [0, 1]$, but Firm 2 cannot. In this case, in any equilibrium, there still exists an $\tilde{x}$ such that all consumers located to the right of $\tilde{x}$ will purchase from Firm 2 and to the left from Firm 1. Then, at $\tilde{x}$, given that Firm 1 can charge a location-specific price $p_1(\tilde{x})$, it must be the case that Firm 1 sets $p_1(\tilde{x}) = 0$, which is Firm 1's marginal cost. Otherwise, Firm 1 can always lower its $p_1(\tilde{x})$ slightly to secure the patronage of the consumers located at $\tilde{x}$ and increase its profit. This means that for any given p_2, we can obtain the location of the marginal consumers for this case of unilateral targeting by replacing p_1 in equation (14.1) with 0, i.e. $\tilde{x} = (p_2+t)/2t$.

To determine Firm 1's prices for consumers located at $x < \tilde{x}$, we note that Firm 1 has no incentives to offer to anyone a price that is lower than what is needed to make a consumer indifferent between buying from Firm 1 and from Firm 2. In other words, the equilibrium $p_1(x)$ is determined by setting $V - p_1(x) - tx = V - p_2 - t(1 - x)$ for $x < \tilde{x}$. Therefore, we should have in equilibrium

$$p_1(x) = \begin{cases} p_2 + t(1 - 2x) & \text{if } x \leq \tilde{x}, \\ 0 & \text{if otherwise} \end{cases} \tag{14.2}$$

Firm 1's payoff is then given by $\pi_1 = \int_0^{\tilde{x}} p_1(x)dx$ and Firm 2's payoff by $\pi_2 = p_2(1 - \tilde{x})$. By taking the first-order condition with respect to Firm 2's payoff,[2] we can easily

[2] Here, we follow the example in Thisse and Vives (1988) to treat Firm 1 as a price follower when it implements targeted pricing because of its pricing flexibility.

determine the optimal price for Firm 2 and hence the optimal pricing schedule for Firm 1. We illustrate this equilibrium of unilateral targeting in Figure 14.1(a).

In this equilibrium of unilateral targeted pricing, Firm 1 is better off, with its profit increasing from $t/2$ in the case of uniform pricing to $\frac{9}{16}t$. From Figure 14.1(a), we can see that Firm 1 is better off for two reasons. First, Firm 1 can tailor its prices to customers based on their strength of preference, offering varying discounts to those who have progressively stronger preferences for Firm 2. This flexibility in pricing helps Firm 1 to increase its market share from $\frac{1}{2}$ to $\frac{3}{4}$ (see Figure 14.1a). This is 'the market share effect'. Second, Firm 1 can also charge progressively higher prices to those who have progressively stronger preferences for its own product. This is 'the price discrimination effect'. Because of these two effects, most practitioners and experts have intuitively come to the conclusion that targeted pricing will always benefit the practicing firm.

However, this need not be the case. In Figure 14.1(a), we get a hint as to why a practicing firm may not benefit in a competitive context. When both firms adopts uniform pricing, they each set their price at t. However, when Firm 1 has the capability of deploying targeted pricing, Firm 2 responds by lowering its price from t to $t/2$ in an effort to counter the threat of targeted pricing from Firm 1. In other words, targeted pricing can potentially trigger more intense price competition. We can see this 'price competition effect' more clearly if we also allow Firm 2 to implement targeted pricing so that we have competitive targeted pricing in the market.

When both firms can set a location-specific pricing schedule, respectively $p_1(x)$ and $p_2(x)$, we can follow the similar steps as in the case of unilateral targeted pricing to derive the equilibrium pricing schedules, which are given below and illustrated in Figure 14.1(b).

$$p_1(x) = \begin{cases} t(1-2x) & \text{if } x \leq \frac{1}{2} \\ 0 & \text{if otherwise} \end{cases} \tag{14.3}$$

$$p_2(x) = \begin{cases} t(2x-1) & \text{if } x \geq \frac{1}{2} \\ 0 & \text{if otherwise} \end{cases} \tag{14.4}$$

In this equilibrium, the market share effect disappears, as the competing firms share the market equally (see Figure 14.1(b)). The price discrimination effect is still present, as we can see from the above pricing schedules. However, it is not strong enough to outweigh the price competition effect. This is reflected in the fact that both firms' pricing schedules are uniformly below t, the price that both firms set in the benchmark case of no targeted pricing. As a result, both firms are worse off with a lower profit of $t/4$.

The fact that competitive targeted pricing could make practicing firms worse off is perhaps not very surprising in hindsight. As pointed out by Corts (1998, p. 321), 'Competitive price discrimination may intensify competition by giving firms more weapons with which to wage their war.' When competing firms all have the flexibility of targeted pricing, they can target each other's customers with great accuracy and efficiency, and they will all have to compete for each individual customer in the market. For that reason, the intensity of price competition increases to the detriment of both firms. Also for that reason, the early studies on competitive targeted pricing, such as Thisse and Vives (1988), Shaffer and Zhang (1995), Bester and Petrakis (1996), Chen (1997), Fudenberg and Tirole (2000), and Taylor (2003), have all come to the same conclusion, in varying

institutional contexts and with different models, that competitive targeted pricing will make practicing firms worse off.

This conclusion, of course, does not bode well for the future of targeted pricing. However, some reflection based on the analysis we have conducted so far tells us that this conclusion is not inevitable. This is because even if the flexibility compels firms to wrestle each other for each customer in the market, it does not give all firms an equal chance to win each wrestling match. In fact, if a firm is a 'Sumo wrestler' to start with, the flexibility may give it a chance to wrestle for each customer and win each customer, too. In that asymmetrical case, the market share effect can be enhanced and the price discrimination effect can be amplified so that the Sumo wrestler can be better off with targeted pricing than without. Then the question is what kind of firms might be Sumo wrestlers? Shaffer and Zhang (2002) address that question.

To illustrate the argument in that article, consider the following simple model where Firm 1 sells a high-quality product and Firm 2 sells a low-quality product. Suppose that all consumers are willing to pay V for a low-quality product, but $V + \theta$ for the high-quality product, where $\theta \in [0, 1]$ follows a uniform distribution. In other words, the willingness to pay for the low-quality product is constant, but that for the high-quality product varies among consumers. For simplicity, we still maintain the assumption that all costs are zero. Thus, if both high- and low-quality firms charge a single price, respectively p_l and p_h, we must have the payoff functions for both firms given respectively by $\pi_l = p_l(p_h - p_l)$ and $\pi_h = p_h(1 - p_h + p_l)$. From first-order conditions, we can easily determine equilibrium prices and profits. They are $p_l = \frac{1}{3}, p_h = \frac{2}{3}, \pi_l = \frac{1}{9}$, and $\pi_h = \frac{4}{9}$. In this equilibrium, the high-quality firm gets two-thirds of the market and the low quality firm one-third.

Now imagine that both firms can costlessly implement targeted pricing. In this case, it is easy to see that in equilibrium the high-quality firm can corner all consumers by charging θ, the premium that a consumer is willing to pay for a high-quality product. The low-quality firm will charge zero (the marginal cost) to all consumers, but sell to none. Here, the low-quality firm makes zero profit under competitive targeted pricing and the high-quality firm's profit is $\pi_h = \frac{1}{2} > \frac{4}{9}$. The high-quality firm is the Sumo wrestler!

The model used in Shaffer and Zhang (2002) is more general than this simple model suggests, and it incorporates the four main features of targeted pricing: individual addressability, personalized incentives, competition and costs of targeting (Blattberg and Deighton, 1991; Schultz, 1994). The model also allows customers to be loyal to different firms in a competitive context and introduces differences in the size of customer groups loyal to the respective firms.

Their analysis shows that a firm can benefit from competitive targeting after all, even if all consumers are perfectly addressable. The firm that commands a larger loyal following, i.e. that has more customers who are willing to pay a premium for its product, will be the one that benefits. This is because under competitive targeted pricing, a firm's expected payoff from consumers who are contested by competing firms comes only from the loyalty that these consumers have for the firm's brand. Although a firm is always able to outbid its competitor for the consumers who prefer its brand, targeted pricing dissipates all potential rents except for the premiums that contested consumers are willing to pay for a brand. Therefore, in an information-intensive marketing environment where a firm's customers are not anonymous to competition, the last line of defense in a firm's battle to acquire or retain a customer is the customers' relative preference for the firm.

In this context, one can readily appreciate the vital importance of individual (rather than average) consumer loyalty in the information age and hence the need for a firm to invest in enhancing consumer brand loyalty through quality, relationship, satisfaction, one-to-one marketing etc.

More recently, Liu and Zhang (2006) have shown that in a channel context, manufacturers are typically such Sumo wrestlers if they are in a position to dictate the wholesale prices for retailers. This is because, without targeted pricing at the retail level, a retailer can always commit to a single price markup and leverage the market coverage to get the manufacturer to charge a low wholesale price. In other words, the retailer can credibly threaten to raise its retail price to all end users automatically and sell to far fewer customers if the manufacturer charges a high wholesale price. To alleviate 'the double marginalization problem', the manufacturer will not charge too high a wholesale price. However, with the ability to implement targeted pricing at the retail level, the retailer loses such a leverage somewhat, as it will use variable markups to sell to end users. This means that the manufacturer can raise its wholesale price without worrying too much about worsening the double marginalization problem.

Of course, the existence of a Sumo wrestler, or asymmetry in competition, is a more obvious situation where a firm can benefit from competitive targeted pricing. A tougher question to answer is, whether in a situation where competing firms are equally matched and they all implement targeted pricing, can any of them become better off? This is a situation where the early literature has shown that the market share effect of targeted pricing disappears and the price competition effect dominates. More recently, however, Chen et al. (2001) have concluded that a firm, indeed all competing firms, can become better off in that situation.

Chen et al. (2001) note that targeted pricing in practice is imperfect in that competing firms can never distinguish different types of customers in a market with certitude.[3] For instance, a firm's own loyal customer may be mistaken for a switcher because of a firm's imperfect targetability. When firms compete with imperfect targetability, what they term the 'mistargeting effect' will be at work, which can help to moderate price competition to the benefit of all competing firms. More concretely, firms always want to charge a high price to price-insensitive loyal customers and a low price to price-sensitive switchers. Due to imperfect targetability, each firm will mistakenly classify some price-sensitive switchers as price-insensitive loyal customers and charge them all a high price. These misclassifications thus allow its competitors to acquire those mistargeted customers without lowering their prices and, hence, reduce the rival firm's incentive to cut prices. This effect softens price competition in the market, which benefits all competing firms. Of course, the magnitude of this effect will depend on targetability, and at a sufficiently high targetability, say perfect targetability, this effect can be weakened to the extent that neither firm can benefit from competitive targeted pricing.

Thus this study narrows down the conditions under which competing firms cannot benefit from competitive targeted pricing. There are two: firm symmetry and (sufficiently) high targetability. In addition, the article points out that imperfect targetability also

[3] Interestingly, Chen and Iyer (2002) show that competing firms may even purposefully underinvest in their targetability so that they do not identify consumers perfectly.

qualitatively changes the incentive environment for competing firms engaging in targeted pricing. For instance, superior knowledge of individual customers can be a competitive advantage, but competing firms may all benefit from exchanging individual customer information with each other at the nascent stage of targeted pricing when firms' targetability is low. Indeed, under certain circumstances, a firm may even find it profitable to give away this information unilaterally. In terms of competitive dynamics, Chen et al. (2001) suggest that competitive targeted pricing does not doom small firms. In fact, targeted pricing may provide a good opportunity for a small firm to leapfrog a large firm. The key to leapfrogging is a high level of targetability or customer knowledge. In other words, small firms can also become the Sumo wrestler if they manage to gain a high level of targetability first.

The literature has also looked into behavior-based targeted pricing. When consumers with varying brand preferences are all passive recipients of a targeted price and they do not react when a firm takes away their surplus, firms can understandably become better off. However, when more and more consumers become aware of the practice of targeted pricing, many of them will start to react to the practice and behave strategically (Feinberg et al., 2002). For instance, a price-insensitive customer may fake being a price-sensitive customer by refusing to pay a high price. In that case, could targeted pricing still benefit a practicing firm? Villas-Boas (2004) offers an intriguing answer to that question.

Villas-Boas (2004) shows that if a firm targets a consumer based on the consumer's past buying behavior and the consumer knows about it, the consumer may start to behave strategically: choosing to forego a purchase today to avoid being recognized as a price-insensitive customer and hence to avail herself of a low price targeted at new buyers. Such strategic waiting on the part of consumers can hurt a firm both through reducing the benefit of price discrimination and through foregone sales. As a result, even a monopoly cannot benefit from targeted pricing.[4] A more recent study by Acquisti and Varian (2005) has come to a similar conclusion from the perspective of the revelation mechanism design, showing that it is never profitable for a monopolist to condition its pricing on purchase history, unless a sufficient number of consumers are not sophisticated enough to see through the seller's targeting strategy or the firm can provide enhanced services to boost consumer valuation subsequent to a purchase. In a competitive context, however, a firm cannot benefit from targeted pricing based on consumer purchase history at all.

Both studies have pointed to the difficulty in implementing price discrimination when consumers can anticipate future prices and make intertemporal adjustments. Without the benefit of price discrimination, targeted pricing will most likely make a firm worse off. However, just as there are reasons to believe that the existence of rational, forward-looking consumers can reduce the benefit of targeted pricing, there are also reasons to believe that their existence may enhance that benefit, too. For instance, in a two-period game, Fudenberg and Tirole (2000) show that a firm always has the incentive to offer discounts to the rival firm's customers who have revealed, through their prior purchase, their preference for the rival firm's product. In other words, once a firm figures out who is buying from whom, the firm always has an incentive to poach the rival's customers with a low price. Anticipating such a poaching discount, consumers should become less price

[4] In an earlier paper, Villas-Boas (1999) also shows that competing firms can all be worse off.

sensitive when they make their initial purchases, and this demand-driven effect should help to sustain high initial prices in the market. These high initial prices in turn should benefit competing firms.

On the supply side, the pursuit of targeted pricing can also generate some strategic benefits. In practice, firms frequently need to 'experiment' with their prices in order to gauge customer price sensitivities. A long stream of research on price experimentation shows that a firm may optimally experiment with its pricing decision at the cost of its current profit in order to enhance the informativeness of the observed market demand, and such information can help the firm to increase its future profit (Kihlstrom et al., 1984; Mirman et al., 1993). Interestingly, Mirman et al. (1994) subsequently show that such information always helps a monopolist, but may be detrimental to competing firms. Chen and Zhang (forthcoming) have recently extended the analysis to the case where firms may experiment with their prices not to gauge an uncertain market demand more accurately but to recognize the individual segments of a certain market demand for the purpose of implementing targeted pricing.

Chen and Zhang (forthcoming) show that the pursuit of customer recognition by competing firms based on consumer purchase history can moderate price competition in a market. This is because, as a firm strives to glean more accurate, actionable customer information for subsequent targeted pricing, it must seek to sell to a small number of customers, or to achieve 'exclusivity'. Exclusivity can come only with a high price, relative to the rival's price, such that not all consumers will purchase from the firm. Consequently, the firm has a strategic incentive to raise its price in its pursuit of customer recognition and price discrimination, to the benefit of all competing firms. In fact, Chen and Zhang (forthcoming) show that, paradoxically, a monopolist can become worse off because of the firm's quest for customer recognition, similar to Villas-Boas (1999), but competing firms can all become better off when they all actively pursue customer recognition. This is because competition amplifies what they term as 'the price-for-information' effect, as with competition the rise in one firm's price will, in turn, induce the increase in the rival's price and vice versa.

From all these discussions, we can draw one clear conclusion about targeted pricing: firms do not automatically benefit from this practice. There are mitigating factors, such as competition, strategic customers and mature markets that would prevent a firm from benefiting from this flexible, competitive form of price discrimination. Only those firms that command customer loyalty through product quality, branding, service, relationship marketing etc., and those that have an information advantage, are positioned to reap the benefits of targeted pricing.

3. What is the optimal targeting strategy?

To benefit from targeted pricing, a firm must target the right customers with the right incentives. Who are the right customers to target with discounts: a firm's own customers or the competition's? The literature has shed a good deal of light on this question.

Intuitively, to any firm, the customers who are currently buying from the competition are those who will deliver incremental sales if they are switched over. Therefore a firm should generate most incremental sales and get the most bang out of its discount dollars if it targets the competition's customers. It turns out that poaching with targeted pricing or the strategy of 'paying customers to switch' can be the optimal strategy in a competitive

equilibrium (Shaffer and Zhang, 1995; Chen, 1997; Fudenberg and Tirole, 2000). This is perhaps why magazines offer new subscribers' discounts, and why AT&T and MCI target each other's customers with switching checks.

However, some reflection here should reveal that this strategy cannot be optimal all the time or for all firms. For instance, MCI may very well benefit from poaching AT&T's customers, as AT&T had a bigger market share and hence more (marginal) customers to lose, but why should AT&T follow the same strategy by poaching MCI's customers? Doesn't it make more sense for AT&T to adopt the strategy of 'paying customers to stay'?

Shaffer and Zhang (2000) develop a model where consumers differ in their preferences and competing firms have different installed customer bases. In this model, firms cannot target individual customers, but only their own or the competition's customer base. From the analysis of this model, they come to the conclusion that the benefits of 'paying customers to switch' do not carry over to markets where competing firms are not equally matched. When firms are asymmetric, it can be optimal for a firm to use the strategy of 'paying customers to stay', but surprisingly the identity of this firm cannot be determined by firm size alone. Either the smaller firm or the bigger firm, but not both, may find it optimal to charge a lower price to its own customers. What determines a firm's targeting strategy is whether the firm's own customers are more price elastic than the rival's customers from the firm's own perspective.

To use the example in Shaffer and Zhang (2000, p. 413) to illustrate the point, suppose Pizza Hut and Domino's can both price-discriminate between own customers and the rival's customers. In this case, we might expect that for both firms, the customers located further away from a firm tend to be more price elastic and the customers located near a firm are more price inelastic. Then, regardless of its market share, each firm should pay customers to switch, poaching the customers on the competition's turf. On the other hand, suppose Domino's delivers, but Pizza Hut does not. Then, because Domino's delivers, customers close to Pizza Hut incur little cost to switch to Domino's, while the cost for Domino's customers (who live far from Pizza Hut) to switch to dining in at Pizza Hut is significant, so that few of them will switch even when offered a substantial discount. In this case, Pizza Hut should pay customers to stay, while Domino's Pizza should pay customers to switch.

The analysis in Shaffer and Zhang (2000) also generates three additional insights into how a firm should implement its targeted pricing. First, the firm with the higher regular price should offer the larger discount (e.g. AT&T will offer a larger discount than MCI). Second, the firm with the higher regular price always pays customers to switch. In other words, if a firm's optimal pricing strategy is pay to stay, it must have the lower regular price, too. However, the converse is not true: depending on parameters, the firm with the lower regular price may either want to pay customers to switch (MCI's strategy) or pay customers to stay (Sprint's strategy). Third, if each firm offers a discount to the same consumer group, the firm that is paying customers to switch will have the higher discount. This partially reflects the fact that it is more difficult to acquire the customers who prefer the rival's product in the first place.

Of course, this clear division of own versus competition's customers loses much of its significance when firms can identify and address each individual customer in the market and all consumers are potentially contested for by all competing firms. In that case, as

shown in Shaffer and Zhang (1995 and 2000), firms need to pursue both offensive and defensive targeting simultaneously: they must offer well-tailored incentives to pay customers to stay as well as to switch.

Concretely, in situations where the targeting cost is quite significant, firms should never target all consumers and they should only target consumers in a well-selected 'targeting zone' – the customers who can be profitably contested. Furthermore, they should target both their own and their competitors' customers in the targeting zone with a certain amount of randomness. As targeting costs decrease, firms should move away from offensive targeting to defensive targeting. The reason is that, as costs decrease, a firm has an incentive to target more of the rival's customers. However, the more it does so, the more consumers with stronger loyalty to the rival's product are targeted, so that offensive targeting becomes less effective in switching these consumers. This explains why the intensity of a firm's offensive targeting should level off as the cost of targeting decreases. In contrast, as a firm's more loyal customers are exposed to the rival's targeting due to a lower targeting cost, the firm faces increasingly more incentives to retain these profitable customers through defensive targeting. For that reason, the intensity of defensive targeting should pick up as the cost of targeting decreases.

One side effect of broad targeting is this phenomenon of massive customer churn, where a large number of customers switch to a less-preferred product because of targeted discounts. Shaffer and Zhang (2000) provide a fresh perspective on this phenomenon and suggest that customer churn need not always cause undue alarm. This is because customer churn results from firms taking chances with their loyal customers in order to capture as much consumer surplus from them as possible. From this perspective, it should not be eliminated. In addition, enhancing consumer loyalty should not always lead to churn reduction. This is because a higher consumer loyalty should also give competing firms more incentives to take chances with their loyal customers. The optimal way to manage customer churn is to engage in more defensive targeting (e.g. loyalty programs) as the cost of targeting decreases.

The cost of targeting and the strength of consumer preferences are but two out of many parameters to which firms should pay attention in adjusting their offensive and defensive targeting strategies. In a recent article, Fruchter and Zhang (2004) develop a differential game of competitive targeted pricing and show that a firm's optimal targeting strategies, both offensive and defensive, depend on its actual market share, the relevant redemption rate of its targeted promotions, customer profitability and the effectiveness of its targeted promotions. In the short run, a firm should operationalize its targeting strategies by adjusting its planned promotional incentives on the basis of the observed differences between actual and planned market shares, and between actual and planned redemption rates. In the long run, a focus on customer retention is not an optimal strategy for all firms in a competitive context. A firm with a sufficiently large market share should focus on customer retention (defensive targeting), whereas a firm with a sufficiently small market share should stress customer acquisition (offensive targeting). This is the case regardless of whether or not the firm is more effective in targeting its current customers. When market shares are more evenly divided, the optimal strategy for a firm is to focus more on customer acquisition than retention.

However, no matter how thoughtful and diligent a firm is in implementing its targeting strategy, it may still be doomed to fail if it ignores the customers' emotional reactions to

Table 14.1 Parameter estimates and effects tests

	Behaviorist	No switching	No loyalty	No betrayal	No Jealousy	Strong	None
		$s = 0$	$l = 0$	$b = 0$	$j = 0$	$bj = 0$	All = 0
s	0.2341	–	0.1434	0.2612	0.1875	0.2300	–
l	0.2040	0.1535	–	0.2416	0.1832	0.2030	–
b	0.1241	0.1950	0.1607	–	0.1679	–	–
j	0.1187	0.0796	0.0539	0.1626	–	–	–
p versus behaviorist	–	*	*	*	*	*	*
p versus strong	*	[a]	[a]	*	*	–	*
p versus none	*	*	*	*	*	*	–

Notes:
[a] As these do not nest the strong-rationality model, they are not directly comparable.
* $p < 0.001$.

Source: Feinberg et al. (2002), table 6.

targeted pricing. When more and more customers become aware of the practice of targeted pricing, a practicing firm cannot simply assume that consumers will calmly accept whatever price a firm imposes on them. Indeed, amazon.com learned the hard way, when it experimented in 2000 with using targeted pricing to sell DVDs and books, that 'Few things stir up a consumer revolt quicker than the notion that someone else is getting a better deal' (*The Washington Post*, 27 September 2000, p. A1). Amazon.com had a PR disaster on its hands when some consumers found out through Internet chat rooms and media reports that they were willfully subjected to higher prices than others who did not necessarily deserve a discount. Should a firm still use targeted pricing when consumers become aware? Feinberg et al. (2002) look into that question.

Through experiments, Feinberg et al. show that consumers care about not only the prices they themselves have to pay, but also the prices other groups of potential purchasers pay at the same firm. As shown in Table 14.1, by comparing statistical results for nested models, Feinberg et al. establish that targeted pricing in a competitive context can generate two behavioral effects among customers. First, 'consumers' preference for their favored firm will decrease if it offers a special price to switchers (the other firms present customers) and not to loyals (their own firm's present customers)'. Because of this, loyals are less likely to purchase from their favored firm. This is what they term as 'the betrayal effect', which has a sizable magnitude of 0.1241, as indicated in Table 14.1. Second, 'Consumers' preference for their favored firm will decrease if another firm offers a special price to its own loyals.' This is 'the jealousy effect', which also tends to reduce the likelihood of consumers' purchases at their favored firm. The magnitude of this effect is comparable to that of the betrayal effect (0.1187). However, the presence of the two effects in the marketplace does not mean that a firm should never use targeted pricing. All it means is that a firm should think through its strategies carefully and take advantage of those effects when they are favorable and mitigate them when they are not. In general, this

involves a firm recognizing these psychological effects and adjusting its targeting strategy from a more offensive-oriented to a more defensive-oriented strategy. This analysis was recently extended by the same authors to an environment of competitive price increase (Krishna et al., 2007).

4. Does social welfare improve?

Many researchers have argued that targeted pricing can potentially harm social welfare (Shaffer and Zhang, 1995; Chen, 1997; Fudenberg and Tirole, 2000). This is because targeted pricing can distort consumer choices and motivate consumers to buy products that are less preferred. By implication, regulatory interventions might be warranted. However, this line of reasoning works only when the market size is fixed, firms do not make any other non-price adjustments because of targeted pricing, and strategic consumers do not exist in the market. In the real world, it would be difficult to find a market where all three conditions are present.

When the size of a market is expandable, it is easy to see why social welfare may improve due to competitive targeted pricing. Targeted pricing will allow all competing firms to lower their prices to 'marginal consumers' who would otherwise not purchase from any firm. The increased sales will increase social welfare, as firms will never sell at a price below its marginal cost and consumers will never purchase a product that does not provide a positive surplus.

Even if the size of a market cannot expand, social welfare can still improve if competing firms make long-term adjustments, say changing their product locations to compete for customers. Lederer and Hurter (1986) investigate that possibility in an elegant, but rather involved, model. Here, we can use a much simpler model to illustrate that possibility.

Consider again the simple Hotelling model that we used in Section 2. Instead of assuming that two competing firms are located at the respective ends of the Hotelling line, we now assume that two firms can choose their respective locations a and b on the line, where $0 \leq a \leq b \leq 1$, before they make their pricing decisions. In other words, firms know each other's locations before they make their respective pricing decisions. To make sure that for any pair of locations (a, b), the equilibrium exists for the pricing game, we further assume that consumer transportation cost is quadratic in the distance traveled. Thus, for a consumer located at $x \in (a, b)$, her utility from buying from Firm 1 and Firm 2 is given by $V - p_1 - t(x - a)^2$ and $V - p_2 - t(b - x)^2$ respectively. We shall maintain all other assumptions about the Hotelling model that we made in Section 2.

As D'Aspremont et al. (1979) have shown, if the two firms are restricted to uniform pricing, each charging a single price, the firms will choose their product locations respectively at 0 and 1 in equilibrium. In other words, the competing firms want to follow 'the principle of maximum differentiation', maximally differentiating themselves to moderate price competition in the market. In equilibrium, the two firms share the market equally, with the indifferent customers being located at $\frac{1}{2}$, and they each charge a price of t. In this market, given that the total demand is fixed, any change in social welfare will depend only on the total disutility (or the total transportation cost) that consumers in the market must suffer, which is $\frac{1}{12}t$.

Now imagine that in this market both firms adopt targeted pricing. Then, for any pair of locations (a, b), if the consumers located at x purchase from Firm 1, the price they are paying must be the premium they are willing to pay for Firm 1's product because of

their location, which is the difference in transportation costs between traveling to Firm 1 and to Firm 2. Thus competitive targeted pricing introduces the incentives for a firm to minimize the costs for consumers to travel to the firm in its location decision, as doing so will allow the firm to charge higher prices subsequently. Then competing firms will choose their locations at $\frac{1}{4}$ and $\frac{3}{4}$ respectively, the locations that will minimize the total disutility in the market. At these socially optimal locations, the total disutility in the market is only $\frac{1}{48}t$ and thus competitive targeted pricing improves social welfare by $\frac{3}{48}t$.

Intuitively, competitive targeted pricing will expose all consumers to competition, and what each firm can charge will depend on how happy individual consumers are about a firm relative to its rival. Therefore firms will have to make customers happy to keep themselves profitable and hence comes social welfare improvement. Clearly, this source of social welfare improvement is generalizable to other situations and even to many other decisions that competing firms have to make. For instance, social welfare also improves by the same amount if firms were to pursue 'the principle of minimum differentiation' prior to the introduction of targeted pricing (Zhang, 1995). It is also likely that because of competitive targeted pricing, a firm's service provisions (Armstrong and Vickers, 2001), marketing expenditures, quality improvements, market entry etc. may also be at the socially optimal levels or close to them (Choudhary et al., 2005; Ghose and Huang, 2006; Liu and Serfes, 2004, 2005).

Finally, as shown in Chen and Zhang (forthcoming), the existence of strategic consumers in the market can also provide an opportunity for competitive targeted pricing to improve social welfare. This is because targeted pricing allows a firm to price-discriminate and hence to discourage strategic consumers from waiting for or foregoing purchases. As a result, sales increase even if no new customer enters the market.

Of course, there could be other reasons on the cost side or demand side as to why targeted pricing may or may not improve social welfare. However, the literature seems to suggest, on balance, that competitive targeted pricing is social welfare improving. At the minimum, there does not seem to be any solid economic ground at this point to call for any regulatory intervention in targeted pricing.

5. Conclusion

Competitive targeted pricing is a practice that is still evolving rapidly. The theoretical research in the past decade or so has generated some insightful perspectives, which allow us to peer into its future, notwithstanding the fact that the literature itself is also fast evolving. From these theoretical studies, we can perhaps draw three general conclusions about competitive targeted pricing.

First, the practice of targeted pricing has gone significantly beyond the traditional concept of price discrimination. With new information technologies becoming available, practitioners are redefining what is feasible in price discrimination and they have broken out of the confines of traditional practices. Looking into the future, we should not be surprised to see more and more sophisticated, unconventional schemes in targeted pricing. Indeed, as we are marching further into the Information Age, only practitioners' creativity, information technologies and consumer privacy concerns can limit the popularity and varieties of targeted pricing.

Second, unlike the conventional practices of price discrimination where the firm is thought always to benefit, competitive targeted pricing does not always benefit practicing

firms. The reason is that better customer targeting by competing firms exposes more consumers to competition. As a result, consumers may all benefit from competitive targeted pricing and social welfare may also improve.

Third, perhaps most interestingly, competitive targeted pricing rewards the 'right' firms with 'right' strategies. The conventional wisdom is that price discrimination benefits monopolistic firms who are deft enough to exploit their market power. In contrast, competitive targeted pricing forces competing firms to contest for, potentially, all consumers. Only the firms that have earned customer liking and command customer loyalty will have the upper hand in winning individual contests and hence benefit from targeted pricing. This cannot help but encourage firms to become more customer and market oriented in the long run.

These three conclusions bode well for the future of competitive targeted pricing. This means that the literature also needs to move forward to facilitate the coming of that future. On the empirical side, a pressing need is to document the benefits of targeted pricing to a firm with some actual performance data, even though from a theoretical perspective there is a compelling logic for such benefits to exist. On the theory side, much research is still needed to understand how targeted pricing may change and interact with other decisions in the marketing mix.

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15 Pricing in marketing channels*

K. Sudhir and Sumon Datta

Abstract

This chapter provides a critical review of research on pricing within a channel environment. We first describe the literature in terms of increasing time horizons of decision-making in a channel setting: (1) retail pass-through (2) pricing contracts and (3) channel design, all of which occur within a given market environment. We then describe the emerging empirical literature on structural econometric models of channels and its use in (1) inferring channel participant behavior and (2) policy simulations in a channel setting. We also discuss potential areas for future research in each area.

'Price' and 'channel' are two of the four elements of the marketing mix that managers control, yet they differ fundamentally in how managers can use them to impact market demand. While price is the most flexible, in that managers can change it most easily to impact short-run demand, the distribution channel through which firms reach their end consumer is the least flexible and perhaps the costliest to change in the short run. Therefore channel design is viewed as part of a firm's long-run strategy. Most importantly, in the presence of a typically decentralized distribution channel, an upstream price change by a manufacturer does not affect consumer demand directly, but only through how this upstream price change affects the retail price set downstream in the channel.

In his review of the pricing literature, Rao (1984) stated that 'the issues of pricing along the distribution channel . . . have not received much attention in the literature'. However, over the last 25 years, this gap has been remedied substantially. The tools of game theory have revolutionized the theoretical analysis of pricing within the channel and clarified the many issues about how prices are set within a channel; more importantly, these analyses have offered insights into the optimal long-term channel strategy, given how prices will be set within the channel. A smaller but emerging empirical literature on structural models of channels has provided insights on the behavior of channel participants and tools to perform policy analysis in a channel setting. The purpose of this chapter is to provide a critical review of this literature, identify the key themes of understanding that have emerged from research to date and identify important gaps in our knowledge that would benefit from future research.

Given the short-run nature of price and the long-run nature of the channel, we organize the literature in terms of three key issues of managerial interest that progressively increase in their time horizons for the decision. The three questions are:

1. Conditional on the distribution channel (which is fixed in the short run) and other market characteristics, how can a change in upstream price affect the downstream price seen by the end consumer? This question of 'pass-through' is the most short

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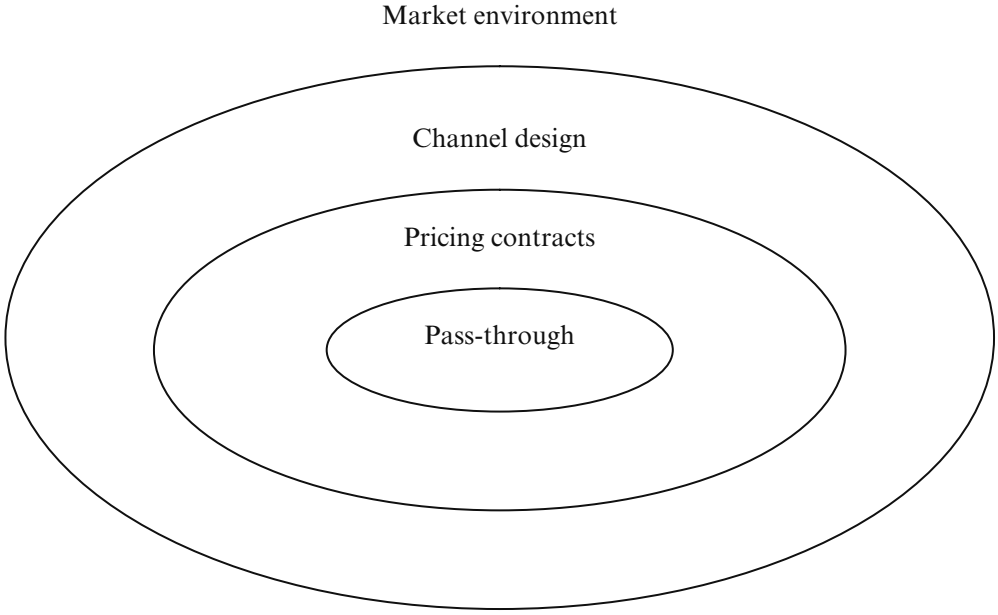

Figure 15.1 Pricing within a channel: key issues

term of the three sets of decisions we consider. Pass-through is of interest to an upstream manager because it determines the extent to which the upstream manufacturer will change prices.

2. Conditional on the distribution channel (which is fixed in the short run) and other market characteristics, what is the best pricing contract to offer to the downstream channel member? This is a medium-term decision, where managers set the 'rules of their interactions' within the existing channel structure. These contracts affect the objective function of the market participants; and managers seek contracts that maximize their profits given a chosen channel structure. Pricing contracts can include linear tariffs, two part-tariffs, quantity discounts, slotting allowances, resale price maintenance (RPM) etc. Note that the types of pricing contracts that can be used may be constrained by law.
3. Finally, given the market characteristics, what is the optimal channel structure and the pricing contract? This is a long-term consideration where managers decide on the nature of channel ownership given the market characteristics. Should a firm vertically integrate or decentralize? Or would a mixed strategy of partial integration, with the manufacturer directly selling along with independent retailers, be optimal? The emergence of the Internet as a sales channel has brought the issue of partial forward integration again into focus in recent years. Since the optimality of the channel structure depends on the nature of pricing contracts that are available to the manufacturer, channel structure design is intimately linked to the pricing strategy.

Finally, all of these decisions are embedded in the market environment in which the firms operate. A schematic way of thinking about these three sets of managerial

decisions embedded within a market environment is given in Figure 15.1, where we have laid out each of these questions within concentric circles. The answers to the pass-through questions are linked to the pricing contracts, which are in turn linked to the questions about channel design, which in turn are linked to the market environment in which the firms operate. Since no one contribution can exhaust all possible combinations within the above framework to give us a complete understanding of the tradeoffs involved, one objective of this chapter is to identify generalizable themes across multiple papers that model different combinations of market environments, channel structures and pricing contracts (see Table 15.1). This exercise should also help us identify key gaps in the literature.

We also describe the complementary empirical literature on structural models of channels that have emerged over the last decade. Such models serve (1) to describe manufacturer–retailer interactions that best describe the market and (2) to perform policy analysis of various channel decisions.

Section 2 describes a basic game-theoretic model of channels to illustrate the key modeling issues. Section 3 discusses the pass-through literature, Section 4 discusses the pricing contracts and Section 5 discusses the literature on optimal channel structures. Section 6 reviews the literature on structural econometric models. Section 7 concludes.

2. An illustrative game-theoretic model of channels: the bilateral monopoly

McGuire and Staelin (1983) laid the foundation for game-theoretic analysis of channels in marketing. At the heart of the channel pricing game-theoretic literature is the concept of double marginalization (Spengler, 1950). The concept is applicable whenever there are multiple decision-makers setting prices in stages; but to make the idea concrete we illustrate double marginalization in the simplest setting of a bilateral monopoly.

Consider the following bilateral monopoly setting as shown in Figure 15.2: a manufacturer who produces at a unit cost c sets a wholesale price w to his retailer who in turn sets a retail price p to the consumer. Consumer demand follows a linear demand model: $q = 1 - p$.

Given the sequential nature of the game, we solve for the optimal retail and wholesale prices by backward induction. We begin by choosing retail price p to maximize the

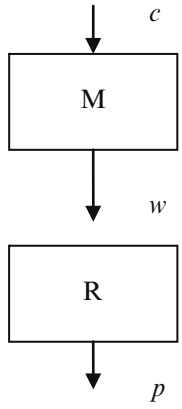

Figure 15.2 A model of bilateral monopoly

Table 15.1 Features modeled in selected papers on channels

Papers	**Market characteristics:** deterministic/ uncertain demand (DD/ UD)); (durable/ nondurable (D/ND)/non-specifiable (NS)	**Manufacturers:** monopoly/ competition (M/C); observed/ hidden action (O/H); non-price action (NP)	**Retailers:** monopoly/ competition (M/C); single/ multiple (SP/MP); observed/hidden action (O/H); non-price action (NP)	**Pricing contract:** linear pricing (LP); 2-part tariff (TT)/ qty discount (QD)/ RPM/slotting allow (SA)	**Model characteristics:** demand model: linear(L)/nonlinear (NL); logit/ exponential/general; manufacturer/retailer stackelberg/vertical Nash (MS/RS/VN)
Jeuland and Shugan (1983)	DD, ND	M, O	M, SP, O	LP, QD	L, MS
McGuire and Staelin (1983)	DD, ND	C, O	C, SP, O	LP	L, MS
Coughlan (1985)	DD, ND	C, O	C, SP, O	LP	L, concave, convex, MS
Choi (1991)	DD, ND	C, O	(C, SP); (M, MP), O	LP	L, NL, MS, RS, N
Trivedi (1998)	DD, ND	C, O	C, MP, O	LP	L, MS, RS, N
Desai et al. (2004)	DD, D	M, O	M, SP, O	TT	L, MS
Iyer (1998)	DD, ND	M, O	C, NP		
Moorthy (1987)	DD, ND	M, O	M, SP, O	TT	L, MS
Ingene and Parry (1998)	DD, ND	M, O	C, non-identical, SP, O	TT	L, MS
Iyer and Villas-Boas (2003)	UD, NS	M, O	M, SP, H	TT, bargaining	NL
Romano (1994)	DD, ND	M, H, NP	M, SP, H, NP	RPM	NL, N
Lal (1990)	DD, ND	C, O	M, MP, O	LP, TD	L, N
Gerstner and Hess (1995)	DD, ND	M, O	M, SP, O	LP, manufacturer rebates/coupons	2 segments of high and low valuation, MS
Lal and Villas-Boas (1998)	DD, ND	C, O	C, MP, O	LP, TD	4 segments, MS
Bruce et al. (2005)	DD, D	C, O	C, SP, O	LP, TD	2 segments of high and low valuation, MS
Moorthy (2005)	DD, ND	C, O	C, MP, O	LP, TD	General, MS

Tyagi (1999a)	DD, ND	M, O	M, SP, O	LP, TD	L, concave, convex, MS
Sudhir and Rao (2006)	DD, ND	C, O	M, MP, O	SA	L
Shaffer (1991)	DD, ND	C, O	C, MP, O	LP, SA, RPM	General, MS
Kim and Staelin (1999)	DD, ND	C, O	C, MP, O, NP	LP, SA	L, MS
Chen (2003)	DD, ND	M, O	C, SP, one dominant retailer, O	TT	General, MS
Dukes et al. (2006)	DD, ND	C, O	C, MP, O	Bargaining	L
Chiang et al. (2003)	DD, ND	M, O, direct channel	M, SP, O	LP	L, MS
Kumar and Ruan (2006)	DD, ND	C, O, direct channel	M, MP, O, NP	LP	2 segments of store/ brand loyal, L, MS
Purohit (1997)	DD, D	M, O	C, SP, O	LP	Rent vs buy, MS

retailer's objective function: $\Pi^R = (p - w)q(p) = (p - w)(1 - p)$. Taking the first-order conditions with respect to p gives

$$\frac{\partial \Pi^R}{\partial p} = 1 + w - 2p = 0 \Rightarrow p = \frac{1 + w}{2}$$

Therefore retail pass-through measured in this model is given by

$$\frac{\partial p}{\partial w} = \frac{1}{2}$$

The manufacturer then chooses wholesale price w to maximize the manufacturer's objective function:

$$\Pi^M = (w - c)q(p(w)) = (w - c)\left(1 - \frac{1 + w}{2}\right) = (w - c)\left(\frac{1 - w}{2}\right)$$

Taking the first-order conditions with respect to w gives

$$\frac{\partial \Pi^M}{\partial w} = \frac{1 + c - 2w}{2} = 0 \Rightarrow w = \frac{1 + c}{2}$$

Hence retail price is

$$p = \frac{1}{2} + \frac{1 + c}{4} = \frac{3 + c}{4}$$

At the chosen retail and wholesale prices, the manufacturer and retailer profits are

$$\Pi^M = \left(\frac{1 - c}{2}\right)\left(\frac{1 - c}{4}\right) = \frac{(1 - c)^2}{8}; \qquad \Pi^R = \left(\frac{1 - c}{4}\right)\left(\frac{1 - c}{4}\right) = \frac{(1 - c)^2}{16}$$

The total channel profit is

$$\Pi^M + \Pi^R = \frac{3}{16}(1 - c)^2$$

As a point of comparison, it is useful to compare the retail prices and total channel profits if the manufacturer owned the retailer and set the final retail price. In that case, the manufacturer's (or the channel's) optimal price is obtained by maximizing $\Pi^c = (p - c)q(p) = (p - c)(1 - p)$. Taking the first-order conditions with respect to p gives

$$\frac{\partial \Pi^c}{\partial p} = 1 + c - 2p = 0 \Rightarrow p = \frac{1 + c}{2}$$

The total channel profit is given by

$$\Pi^c = \frac{(1 - c)^2}{4}$$

The total profit from the vertically integrated channel is therefore greater than profit from the decentralized channel.

The key takeaways from the above model are: first, the price in the vertically integrated channel is lower than the price in the decentralized channel; i.e. in the decentralized

channel the retail price is distorted upward from the price that would be observed in the integrated channel. At each stage the monopolist marks up the price; therefore in the integrated channel there is only one monopoly markup, while there are two markups in the channel (one by the manufacturer and one by the retailer). This 'double markup' is referred to as the 'double marginalization' and lends itself to the joke: 'From the consumer's point of view, what is worse than a monopoly? A chain of monopolies.' Second, the total channel profit with vertical integration is greater than the profits in the decentralized channel; therefore in this case, it would be optimal for the manufacturer to set up an integrated channel if it were feasible. Finally, given that $\partial p/\partial w = 1/2$ in equilibrium, only 50 percent of the change in wholesale prices is passed through to the consumer.

In this model, we allowed for only a linear price contract between the manufacturer and the retailer. Suppose the manufacturer could use another contract such as a two-part tariff, where the retailer pays not only a unit cost, but also a fixed fee. In such a scenario, it is easy to see from the earlier analysis that the optimal strategy for the manufacturer would be to set the wholesale price at the manufacturer's marginal cost c, and the retailer would set the price at the vertically integrated retail price of $(1 + c)/2$. The manufacturer can then extract the entire profits that would result $[(1 + c)^2]/4$ in the form of fixed fees. Thus, using a two-part tariff, the manufacturer can obtain the vertically integrated channel outcome without having to integrate the channel.

The above illustrative model outlines the issues involved in the three managerial questions raised in the introduction. First, the pass-through with either a linear contact or two-part tariff is 50 percent. Second, the optimal pricing contract for the manufacturer between a unit price and two-part tariff is the two-part tariff. Finally, the profit from the vertically integrated channel and the bilateral monopoly structure is identical for the manufacturer when allowing for both a linear price contract and two-part tariff. But if the manufacturer is restricted to a linear price contract, the total channel profit is greater with a vertically integrated structure.

In the bilateral monopoly model above, a single manufacturer sold a single product at a linear unit price to a single retailer, who in turn sold only that product to the end customer. The demand was modeled using a linear demand model. It was also deterministic, and so there was no uncertainty about the market demand. Finally, manufacturers and retailers had no ability to affect demand, except through the change in price.

Markets of course can differ on every one of the dimensions described above. For instance, there could be competition among manufacturers, and competition among retailers. Each manufacturer or retailer could sell more than one product. Market participants may use objectives such as category profit maximization or only choose to maximize profits of any given product without considering the externalities on other products.

Rather than a linear price, the manufacturers could use other pricing contracts. Examples include nonlinear quantity discounts and two-part tariffs, which are common among franchisers. They could also impose a maximum retail price that retailers can charge, i.e. employ resale price maintenance (RPM). In the short term, they could also offer trade promotions or slotting allowances that involve transfers from manufacturers to the retailer.

Finally, uncertainty in demand can be important. If manufacturers and retailers can affect demand through their actions such as better service, then in the presence of demand uncertainty, the issue of whether participants put in the optimal level of effort to create

Table 15.2 Key characteristics modeled in current research

Channel structure	Manufacturers	• Monopoly/competition • Single/multiple products • Observability of actions
	Retailer	• Monopoly/competition/provision of exclusive territories • Single/multiple products/provision of exclusive dealing • Observability of actions/types
Pricing contracts		• Linear pricing • Two-part tariffs • Quantity discount • Resale price maintenance • Trade promotions • Slotting allowances
Market environment		• Deterministic versus uncertain demand • Relative power between manufacturers and retailers • Presence of store brands • Appropriate model of demand: linear, logit, exponential etc.

demand becomes a challenge. The issues of moral hazard and free-riding in terms of services at both the manufacturer and retailer level becomes critical. Researchers have also observed that the functional form used to model demand affects retail pass-through and optimal equilibrium strategies. Indeed, the range of possible institutional and market characteristics is very large. We summarize the key characteristics that have been modeled in current research in the Table 15.2 above.

3. Retail pass-through

The theoretical literature on pass-through follows two broad streams. The first stream assumes that manufacturers change wholesale prices in response to changing demand and cost conditions (e.g. Moorthy, 2005). The second is based on the price discrimination motive; here trade promotions serve to price-discriminate between price-sensitive and brand-loyal customers (e.g. Lal and Villas-Boas, 1998). In practice, both reasons coexist in the market. Empirical research typically has not drawn a distinction between the different reasons.

3.1 Models where wholesale price changes due to changes in demand and costs

As in our illustrative example in Section 2, own pass-through for a product, j, is typically measured using the comparative static $\partial p_j/\partial w_j$ (e.g. Tyagi, 1999a; Sudhir, 2001; Moorthy, 2005). With multiple products, the extent to which a retailer changes the price of another product i in response to a wholesale price change for product j is termed cross pass-through and is operationalized as $\partial p_i/\partial w_j$.

The literature has highlighted five factors that affect pass-through: (1) retailer objective/pricing rule; (2) demand characteristics; (3) manufacturer–retailer interaction; (4) manufacturer

competition; and (5) retail competition. We organize the discussion of the results along these factors. Table 15.3 provides a summary of the key results in the literature.

Depending on the retailer's sophistication, a retailer may use a simple markup rule (a constant markup would imply 100 percent own pass-through and 0 percent cross pass-through) or maximize profits. The theoretical literature on pass-through is based on the assumption that the retailer maximizes a profit objective. Retailers may maximize brand profits, category profits, or, when cross-category effects are important, profits across categories.

A profit-maximizing retailer sets the retail price where marginal cost equals marginal revenue. A reduction in the wholesale price reduces the retailer's marginal cost, and therefore it must reduce its price to reduce its marginal revenue by the same amount. As the responsiveness of the marginal revenue to a change in retail price depends on the concavity of the demand function, the change in retail price corresponding to a change in wholesale price, or the pass-through, depends on the functional form of demand (Lee and Staelin, 1997; Tyagi, 1999a).[1]

Lee and Staelin create a typology of vertical strategic interactions between channel members with pass-through between 0 and 100 percent ($0 < \partial p_i/\partial w_i < 1$, which they refer to as vertical strategic substitutability), pass-through over 100 percent ($\partial p_i/\partial w_i > 1$, vertical strategic complementarity) and pass-through of 100 percent ($\partial p_i/\partial w_i = 0$, vertical strategic independence). Tyagi characterizes demand functions with pass-through greater than or below 100 percent in terms of the convexity of the demand curve. While standard demand functions, such as the linear and the logit (or any concave function), lead to vertical strategic substitutes, the multiplicative demand function (and other, but not all, convex demand functions) leads to vertical strategic complements (also see Sudhir, 2001). When a retailer carrying multiple products maximizes category profits, the magnitude of own pass-through is independent of the product's market share in a linear demand specification (Shugan and Desiraju, 2001) but is inversely proportional to own share in a logit demand specification (Sudhir, 2001).

The level of competition between manufacturers (or products from the same manufacturer) affects cross pass-through. Shugan and Desiraju (2001) show that with a linear demand function the cross pass-through depends on the substitutability of the products. If the cross-price slopes are asymmetric, then cross pass-through will be positive for one product and negative for the other, depending on the direction of asymmetry.

In terms of the effect of manufacturer–retailer relationship on pass-through, the three common relationships studied are: (1) manufacturer Stackelberg, where the manufacturers set the wholesale prices and the retailer takes these wholesale prices as given when setting the retail price; (2) vertical Nash, where manufacturers and retailers set prices simultaneously; and (3) retailer Stackelberg, where the retailer sets the retail price and the manufacturer responds with a wholesale price.

Finally, Moorthy (2005) extends the pass-through results to the case of competing retailers (see also Basuroy et al., 2001). Moorthy studies both the linear and nested logit model,[2]

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[1] See Tyagi (1999a) for a more detailed explanation as to how the demand function influences pass-through.

[2] In the nested model, consumers make a retailer choice in the first stage and a brand choice in the second stage.

Table 15.3 Summary of pass-through results in the literature

Paper	Market structure	Demand model	Vertical strategic interaction	Retailer objective	Implications for own-brand pass-through ($\partial P_j/\partial w_j$)	Implications for cross-brand pass-through ($\partial P_i/\partial w_j$)
Besanko et al. (1998)	Multiple manufacturers, single retailer	Homogeneous logit	Vertical Nash	Maximize category profits	• Equal to 1	• Equal to 0
Tyagi (1999a)	Single manufacturer, single retailer	Linear; concave; convex	Manufacturer Stackelberg	Maximize profits (only one product)	• Greater or less than 100% depending on demand model	• Not applicable (only one product)
Sudhir (2001)	Multiple manufacturers, single retailer	Homogeneous logit	Manufacturer Stackelberg	Maximize category profits	• Between 0 and 1 • Inversely proportional to own share s_j	• Between 0 and −1 • Magnitude is directly proportional to promoting brand share s_j • Unrelated to s_i
		Homogeneous logit (two brands + outside good)	Manufacturer Stackelberg	Maximize brand profits	• Positive • Inversely related to own share s_j	• Positive • Magnitude is directly proportional to promoting brand share s_j • Directly related to s_i
Shugan and Desiraju (2001)	Multiple manufacturers, single retailer	General linear	Not specified	Maximize category profits	• Between 0 and 1 • Does not vary with share	• 0 if cross-price effects in demand are equal • Positive or negative, depending on direction of asymmetry in cross-price effects in demand • In a product pair cross-brand pass-through rates have opposite signs

Moorthy (2005)	Two manufacturers and two retailers	Linear demand Hotelling-like model	Manufacturer Stackelberg	Maximize category profits	• Between 0 and 1 w/o retail competition	• Positive with retail competition • Without retail competition, brand asymmetry needed for cross-pass-through, positive for stronger brand and negative for weaker brand
	Two manufacturers and two retailers	Nested logit	Manufacturer Stackelberg	Maximize category profits	• Positive	• Negative cross pass-through w/o retail competition • Can be greater or less than 100% depending on demand model

and arrives at a large number of results on pass-through and cross pass-through. For the nested logit model, which brand gets a greater pass-through from a retailer depends not so much on its strength *vis-à-vis* the other brand (as in Sudhir, 2001), but rather on the relative strengths of the brands at the two retailers. In particular, he finds that pass-through at a retailer for the nested logit model can be greater than or less than 100 percent, depending on whether the brand has lower or greater market share at that retailer.

Moorthy's results show that pass-through for a brand is linked to the extent of retail competition in the market. If retail competition is limited, as is probably true in categories that are not major drivers of store traffic, one can use the predictions of the single retailer models. For categories that drive store traffic, retail competition can be critically important, and therefore the extent of pass-through needs to consider relative brand strengths at the retailers.

Cross pass-through also depends on the extent of retail competition (see Table 15.3 for key results). Moorthy also discusses the cases when wholesale price changes are retailer specific or common across retailers. When wholesale price changes are retailer specific, own pass-through is less than 100 percent and cross pass-through is always negative. But when wholesale price changes are common, cross pass-through can be positive or negative. These differences in results suggest intriguing possibilities about how manufacturers should time trade deals (synchronously or asynchronously) to different retail chains within the market.

3.2 Models where wholesale price changes induce price discrimination

Varian (1980) and Narasimhan (1988) introduce models that seek to discriminate between brand-loyal and price-sensitive customers through promotions. In these models, promotions are characterized as mixed-strategy equilibria. Hence wholesale prices may change with the motive of price discrimination and not necessarily as a result of changes in demand or costs. In contrast to the models that are concerned with demand functional forms (or models like the Hotelling model that generate linear demands), the analytical literature on price discrimination explicitly models consumer segments in terms of their price sensitivity and loyalty.

Lal and Villas-Boas (1998) study price promotions in the context of two competing retailers. Consumers may be loyal to manufacturers, retailers, both or none. A retailer is guaranteed retailer-loyal customers (denoted by R) and the brand-retailer-loyal customers who are committed to the brand (manufacturer) and the retailer (MR). But the retailer has to compete for brand- or manufacturer-loyal customers (M) who are not loyal to a particular retailer, and the completely price-sensitive customer group who are neither loyal to a brand nor to a retailer (S). Whether to promote a high-priced brand is based on the relative ratio of the customers the retailer has to fight for (M), relative to the guaranteed customers (MR). In contrast, the decision to promote a low-priced brand is based on the relative ratio of the customers the retailer has to fight for ($M + S$), relative to the guaranteed customers ($MR + R$). The main insight of the paper is that the retailer has the incentive to promote the higher-priced brand when $(M/MR) > (M + S/MR + R)$.

Thus the decision to pass through a trade deal for the retailer is based on the extent of both retailer and brand loyalty. Interestingly, retailer loyalty has the opposite effect of brand loyalty. Greater brand loyalty allows greater pass-through, while greater retailer loyalty reduces pass-through. Note that these results about how brand loyalty affects

pass-through are critically dependent on retail competition. If there were no retail competition, brand loyalty would not lead to greater pass-through, because the retailer would find the brand-loyal customer to be captive and only the price-sensitive customer needs to be wooed by price promotions.

Kumar et al. (2001) suggest that information asymmetry between customers and firms might be a reason for low pass-through. In a model where customers differ in their valuations and have search costs to find the lowest price, they argue that retailers will pass through a trade promotion only probabilistically in a mixed-strategy equilibrium. This is because in any given week, the consumer may not know if a better price may be available at another retailer who may pass through the trade promotion. The authors show that manufacturers can increase pass-through by advertising their trade promotions to consumers. This relationship between asymmetry and pass-through is consistent with the findings in Busse et al. (2006), who show that pass-through increases when asymmetric information is reduced in the context of trade promotions versus consumer promotions in the car market.

Another suggestion about how to improve pass-through is made in Gerstner and Hess (1991, 1995). They show that manufacturers can use consumer rebates (pull promotion), targeted towards the low-valuation segment, in combination with trade promotions (push promotions) to improve pass-through. Consumer promotions increase the low-valuation segment's willingness to pay. This encourages retailers to participate in trade promotions and serve this segment. Also, consumers are better off with retail price reductions motivated by trade promotions than with large consumer rebates alone. With only consumer rebates, the retailer increases the retail price by the value of the rebate so that the consumer has to pay a higher price in addition to the transaction cost of using the rebate.

3.3 Empirical results on pass-through

Empirical research on pass-through has mostly been on grocery markets, because of the availability of data. Theoretical models show that pass-through is affected by retail competition. But for groceries, even though there is retail competition at the basket level (Bell et al., 1998; Gauri et al., 2007), retail competition is not as strong at the individual-product level (Walters and MacKenzie, 1988). Hence a significant body of empirical research on pass-through has assumed a monopoly retailer.

Based on research in Chevalier and Curhan (1976), Curhan and Kopp (1987/88), Walters (1989) and Blattberg and Neslin (1990), Blattberg et al. (1995) conclude that the finding, 'pass-through rates are less than 100 percent', is an empirical generalization. However, Armstrong (1991), Walters (1989) and Besanko et al. (2005) find that pass-through rates can be greater than 100 percent for certain products. While Armstrong and Walters use a multiplicative functional form for demand (which, as we discussed earlier, leads to greater than 100 percent pass-through), Besanko et al. estimate a reduced-form regression for pass-through across products in several categories without making any assumptions about the functional form of demand or retailers' objectives (category or brand profit maximization). For a single store chain, they find that pass-through rates are greater than 100 percent for 14 percent of the products. In most categories, brands with larger market shares get greater pass-through, suggesting the effect of differences in manufacturers' bargaining power on pass-through. Pass-through rates are also found to

be greater in markets with older and more ethnic populations and in markets with larger households and greater home values. This may be an evidence for the findings of Lal and Villas-Boas (1998) if consumers in these markets have low retailer loyalty.

Does retail competition affect pass-through? Besanko et al. find that distance from the competitor does not affect pass-through. While one possible interpretation of this result is that retail competition has no impact on pass-through, the more likely explanation is that retailers of the same store chain do not adjust their prices across stores because of practical difficulties of having different specials at different stores. In fact, Besanko et al. find that only 2 percent of their pass-through variations can be explained by price zones. But the result that brands with greater market shares have greater pass-through offers indirect support for the role of retail competition. If market shares are correlated with strong brand loyalty, then the result that brands with stronger market share get greater pass-through suggests that retailers do consider retail competition when deciding on pass-through (see the discussion in Lal and Villas-Boas, 1998). Alternatively, this could be because the retail chain is weaker for the brands with the larger market share (Moorthy, 2005). Additional research needs to resolve these alternative reasons for the empirical results.

How do retailer objectives affect pass-through? The retailer objective affects the magnitudes of own and cross pass-through, and, in case of a logit demand specification, even the sign of the cross pass-through. Sudhir (2001) shows that, without retail competition, the cross pass-through is negative for category profit maximization and positive for brand profit maximization. He finds that category profit maximization by the retailer fits the price data better than brand profit maximization for the analyzed categories. Basuroy et al. (2001) evaluate how pricing behavior changed when a retailer shifted from a brand management to a category management behavior. They find that retail pricing in terms of own and cross pass-through changed in a manner predicted by the theory, suggesting that a manufacturer should take into account the retailer's price-setting rules when setting optimal wholesale prices.

A retailer could strategically vary its pricing strategy over high and regular demand periods. Chevalier et al. (2003) show that retail margins for specific goods fall during peak demand periods for that good. Meza and Sudhir (2006) account for the differences in levels of demand and price sensitivity between regular and high demand periods, and show that pass-through varies over the year and the average measures of pass-through for the entire year may be misleading. They use two categories: tuna, which has peak demand during Lent, and beer, which has peak demand during holiday and major sports weekends, to study differences in pass-through between high- and low-demand periods. They find an interesting difference between the two categories. Tuna's peak demand is not correlated with peak purchases in other complementary categories. Hence, while a tuna promotion can draw customers into the store, it does not provide many spillover benefits. In contrast, peak beer demand is correlated with peak purchases in complementary high-margin categories such as snacks. Hence the benefit of passing through promotions is greater for beer than for tuna during peak periods, and accordingly pass-through is greater for beer than for tuna during peak demand. Further, they find that retailers follow a narrow but deep pass-through strategy (only pass-through for the most popular size/brand 'pull items') in regular periods, but a broad but shallow pass-through strategy (lower but similar pass-through for all items) in peak periods.

With respect to cross pass-through, Besanko et al. (2005) find that about two-thirds of the cross pass-through effects are statistically different from zero. Slightly more than one-third of these effects are negative, while slightly less than one-third are positive. However, McAlister (2007) shows that these significant effects do not exist once we account for the high correlation in prices (0.9) across the stores in the data. Essentially, she argues that these significant effects are an artifact of the additional degrees of freedom due to using repeated price observations at the zone level (that do not vary independently over time). Hence further research is required on cross pass-through effects. One possibility as to why the cross pass-through effects are insignificant could be because extant pass-through research has not included prices from competing retailers in the model (as argued by Moorthy, 2005). Future research needs to study cross pass-through effects in greater detail.

Busse et al. (2006) show support for the information asymmetry effect on pass-through in the car market and may be considered indirect support for the findings of Kumar et al. (2001). They show that consumers obtain about 70–90 percent of the value of a consumer rebate, while they get only about 30–40 percent of a dealer promotion. As the authors acknowledge, the result is also consistent with a prospect theory argument. When consumers see a consumer promotion, the reference price shifts downwards, but with a trade promotion, the consumer is unaware of the price discount and the reference price is not affected. This differential effect on consumers' reference prices may explain the differences in pass-through. Future research needs to separate the role of consumer reference point effects and information asymmetry on pass-through.

3.4 Future research

In practice, price discrimination and demand and cost changes both affect wholesale prices. The extant analytical literature on pass-through has studied these cases separately, but it would be worthwhile to see how the predictions might change when both of these effects coexist, as in real markets. This can help create better hypotheses of pass-through in future research. In terms of empirical research, structural models that simultaneously develop both the demand side and the supply side (e.g. Villas-Boas and Zhao, 2005) could potentially incorporate heterogeneity in consumers' price sensitivity or brand and retailer loyalty, and thus tie in the price discrimination motive along with cost changes on the supply side. As we discuss in a subsequent section, a structural model to this effect would not only enable us to test some of the theoretical predictions but would also allow us to perform counterfactual simulations to understand channel member reactions and their impacts under different scenarios.

Several issues are important to address in empirical research on pass-through, for example: (1) how does retail competition affect pass-through?; (2) how does demand specification (brand/retailer loyalty; functional forms etc.) affect pass-through?; (3) how does pass-through behavior vary across categories?; (4) how does pass-through change over time?; (5) how is pass-through measured?; (6) how does pass-through behavior differ across types of trade promotions?

Moorthy (2005) and Lal and Villas-Boas (1998) have shown how pass-through is critically dependent on the extent of retail competition. Empirical research on pass-through has mostly assumed that retail competition is not strong at the individual product level (Walters and MacKenzie, 1988). Further, data from multiple competing retailers are hard

to obtain. Hence empirical evidence for the effects of competition is scarce. However, there could be variations in shopping behavior, across categories within consumers' shopping baskets. For example, a consumer might always buy her produce from the same retailer but search across retailers for best prices on paper goods. Such category-based consumer shopping behavior would be critical for a retailer whose objective is to maximize profits across categories. The issue of share-of-wallet across retailers and its influence on pass-through, for different categories and different retail formats, has not been sufficiently explored. Such analysis would of course require a rich dataset that has information on consumer behavior at a disaggregate level, and across retail chains and retail formats. Future research needs to investigate the implications of retail competition either directly, by acquiring data across competing retailers, or indirectly, by appropriately approximating retail competition in terms of geographical locations of consumers and retail stores of the same or different formats in the market.

For retail competition it is important to consider the differences in retail formats. On the cost or the supply side, this is important because manufacturers could use nonlinear pricing contracts (as we discuss in the next section) which could result in different marginal costs for different retailers and, hence, different pass-through behaviors. In addition, manufacturers could time trade deals synchronously or asynchronously to different retailers, which has different implications for pass-through (Moorthy, 2005). Also, as we have seen, pass-through varies over regular and peak demand periods. The extant literature on pass-through has assumed that the manufacturer and the retailer marginal costs are independent of order quantities and frequencies. If the operating costs of the manufacturer and the retailer are misaligned, or if they are different for different retailers (as may be the case for supermarkets versus club stores), this could have implications for pass-through when demand varies over time.

On the demand side, brand and retailer loyalty and competition could vary across store formats. For example, consumers who tend to visit supermarkets may be less price sensitive, and more retailer or brand loyal, whereas consumers who frequent discount or club stores could be more price sensitive, and less retailer and brand loyal. There could be such idiosyncratic differences in consumers across retail formats because of the different assortment of products in different store formats or because of their different pricing policies (e.g. small pack sizes versus bulk quantities and Hi-Lo versus EDLP). This could have some interesting implications for the nature of competition between different formats and the resulting pass-through behavior across retail formats and brands. Further, retailer and brand loyalty may differ over time as infrequent customers enter markets in peak periods. Systematic research needs to be done across store formats and time to test some of the existing theories and to present managers with descriptive insights into pass-through. For instance, most store chains have a loyalty program. Analysis of store loyalty card data, in conjunction with the overall sales data, could be used to test some of the conclusions in Lal and Villas-Boas (1998).

As the analytical literature has shown, results on pass-through are conditional on the demand-functional forms. Hence adopting specific structural models in empirical research could impose specific constraints on possible pass-through rates. A systematic investigation of which functional forms are supported in the pricing and pass-through data in a given setting can be useful to understand which models should be used for decision support systems for setting wholesale and retail prices.

Pass-through has been measured in many ways. Much of the theoretical literature has focused on the comparative static $\partial p_i/\partial w_i$ to study pass-through (e.g. Tyagi, 1999a), while some has looked at the proportion of trade deals passed through (Kumar et al., 2001). In the context of forward buying and consumer stockpiling, one may need a different definition of pass-through such as the fraction of the total discount that gets passed through to the consumer. Meza and Sudhir (2006) show that using the weighted average wholesale price (rather than the true current promotional price) gets us closer to a true estimate of pass-through in the presence of forward buying and stockpiling than the actual prices. Testing this using data on true marginal wholesale price and actual shipping data as in Abraham and Lodish (1987) and Blattberg and Levin (1987) would be useful validation of extant research using readily available weighted average wholesale price.

Lal et al. (1996) study forward buying, merchandising and trade deals in a single retailer context. They find that while such forward buying reduces pass-through for manufacturers, it is beneficial for manufacturers because it reduces competition among them. Future research should look at how these effects manifest in terms of pass-through when there is retail competition.

Pass-through research has mostly been on grocery markets. It is obvious that there are interesting issues in the context of durable goods, services, industrial buying situations etc. As discussed earlier, Busse et al. (2006) is an exception. Bruce et al. (2005) note that secondary markets matter with durable goods. They find that trade promotions can mitigate the double marginalization problem better for manufacturers of more durable goods. In their model, retailers do not compete with each other. Hence, how these results translate in markets with retail competition needs to be investigated.

Much research on pass-through is based on off-invoices, with unconditional wholesale price reductions. Gomez et al. (2007) study different types of trade deals. They find that only 25.9 percent of discounts are off-invoices. Scanbacks and accruals (31 percent) are negotiated with retailers; these require retailers to attain a quantity level to get the allowance. Scanbacks and accruals may therefore be considered similar to a quantity discount in terms of our discussion of pricing contracts below. Billbacks (3.1 percent) are similar to scanbacks, but based on items that are purchased, not sold, and therefore leave open the option for forward buying. A systematic investigation of how pass-through changes when different pricing contracts are used would be a very useful area of research.

4. Optimal pricing contracts

Manufacturers (or upstream firms) can decide the pricing contract they offer to the retailer (or downstream firm). Researchers have evaluated a number of pricing contracts such as linear wholesale price, quantity discounts, two part-tariffs and resale price maintenance. Typically, the upstream manufacturer structures the pricing contract in a way that is most profitable for it. When the upstream firm does not have the power (for example with large retailers), either the downstream player will set the terms of the pricing contract or it may be an outcome of bargaining negotiations.

4.1 Linear wholesale prices

The simplest and most common pricing contract is the linear wholesale price. This leads to the familiar double marginalization problem discussed in the illustrative example of Section 2. The double marginalization problem results in lower total channel profits (the

size of the pie) than what it could have been under channel coordination. A long stream of literature on channels of distribution has emphasized pricing contracts where the double marginalization problem can be minimized and the channel can be coordinated.[3] We discuss these contracts below.

4.2 Quantity discounts and two-part tariffs

Quantity discounts and two-part tariffs can coordinate the channel. With quantity discounts, the per-unit costs to the retailer fall with quantity purchases. Jeuland and Shugan (1983) show that quantity discounts can be used as a means by which a manufacturer can coordinate the channel in a bilateral monopoly setting.

Moorthy (1987) argues that the Jeuland–Shugan quantity–discount coordination requires only that the retailer's marginal cost equal the marginal revenue at the channel's optimal quantity; its value at quantities other than the channel's optimal quantity can be almost anything. This leeway in choosing the retailer's effective marginal cost away from the channels' optimal quantity leads to a variety of potential pricing schemes (e.g. two-part tariff) that can also be optimal. In a two-part tariff, the retailer makes a fixed payment and pays a per-unit charge for the product. The fixed fee and the per-unit charge are set such that the sales volume and total profit of the channel members is the same as when maximizing total channel profit. For instance, in the bilateral monopoly model discussed in Section 2, the manufacturer can set the wholesale price (w) equal to his marginal cost (c) and then extract the retailer's profit completely with a fixed fee. This will maximize total channel profit and also help the manufacturer maximize his profit.

Researchers have shown that two-part tariffs can be optimal in a wide range of market scenarios such as (1) when retailers have to provide non-contractible services as with franchising services with potential for moral hazard as in Lal (1990); (2) when retailers have to complement the product with another input and then sell a composite output (Vernon and Graham, 1971); (3) when retailers carry a product line (Villas-Boas, 1998); (4) when there is demand uncertainty (e.g. Rey and Tirole, 1986); (5) when manufacturers and retailers have private information (e.g. Desai and Srinivasan, 1995; Tirole, 1988, p. 176).

Iyer and Villas-Boas (2003) however argue that two-part tariffs are not optimal if the product is not completely specifiable. They show that in a model of bargaining between manufacturers and retailers when products are not completely specifiable and demand is uncertain (as is typical in almost all channel models, they also assume retail actions are unobservable), two-part tariffs will not be a part of the market contract even in a simple one manufacturer–one retailer channel. This is because the fixed fee in the two-part tariff does not affect the opportunistic behavior on the part of the manufacturer and, therefore, will not be accepted by the retailer. In their bargaining model, a linear wholesale price contract emerges as the equilibrium outcome. They also note that empirically the use of

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[3] Channel coordination can also be brought about by non-pricing mechanisms. For a simple bilateral monopoly case, Shugan (1985) shows that implicit understandings between channel members can be a partial substitute for formal agreements. Also see Fugate et al. (2006) for a discussion on the different types of coordination mechanisms.

two-part tariffs is considerably small, despite prior findings in the theoretical literature about the optimality of two-part tariffs in a broad range of settings.[4]

When else might a two-part tariff or a quantity discount not work? Ingene and Parry (1995a, 1995b, 1998, 2000) have studied the case of a manufacturer setting a wholesale price schedule for its retailers who differ in their demand and cost structures. They show that when these non-identical retailers compete on price, channel coordination can still be achieved with an appropriately specified quantity discount schedule but not with a simple two-part tariff. A quantity discount schedule can be designed such that the effective marginal cost is different for different retailers and is equal to their marginal revenue, given their differences. In contrast, a two-part tariff offers each retailer the same per-unit charge. Since the Robinson–Patman Act does not allow manufacturers to discriminate between different retailers by charging retailer-specific wholesale prices, a menu of two-part tariffs, where retailers can select whichever tariff they want, can overcome this legal problem, and also coordinate the channel. Interestingly, the authors show that, from the perspective of a profit-maximizing manufacturer, a non-coordinating 'Sophisticated Stackelberg' two-part tariff that simultaneously optimizes the per-unit fee and the fixed fee in light of the difference in retailers' fixed costs may be preferred over channel coordination. The optimal pricing policy is dependent on (1) the retailers' fixed costs, (2) the relative size of the retailers, and (3) the degree of retail competition.

Models in marketing typically assume the manufacturer and retailer marginal costs as constant and fixed. There is a literature at the interface of marketing and operations that addresses optimal pricing contracts when it affects retailer operating costs. When the operating costs of the retailer and the manufacturer are a function of the order quantities, the manufacturer needs to motivate the retailer to choose both retail prices and order quantities that will simultaneously maximize the retailer's profit and the joint profit of the retailer and the manufacturer (Weng, 1995). A simple quantity discount cannot achieve this, and the manufacturer will have to use a fixed franchise fee in combination with the quantity discount. When a supplier caters to multiple non-identical retailers, Chen et al. (2001) show that the same optimum level of channel-wide profits as in a centralized system can be achieved in a decentralized system, but only if coordination is achieved via a unique wholesale pricing policy – periodically charged fixed fees, and a discount pricing scheme under which the discount given to a retailer is the sum of three discount components based on the retailer's (i) annual sales volume, (ii) order quantity, and (iii) order frequency.

4.3 Resale price maintenance (RPM)

RPM is a method of vertical control where the upstream firm dictates pricing policies at subsequent stages of the distribution channel. By setting a price ceiling (maximum RPM), the upstream firm can control the retailer's margin, so that it can eliminate the double marginalization problem and reduce the retail price. Setting a price floor (minimum RPM) can also achieve channel coordination by reducing price competition

[4] Through a laboratory experiment, Ho and Zhang (2008) show that, with a reference-dependent utility function, retailers perceive the up-front fixed fee in a two-part tariff as a loss, and the subsequent sales proceeds as a gain. Hence, if retailers are loss averse, a two-part tariff may not be able to coordinate the channel.

among retailers and diverting competition into non-price dimensions such as service (Telser, 1960; Mathewson and Winter, 1984; Iyer, 1998) or product quality (Marvel and McCafferty, 1984).[5]

The issue of RPM is pertinent in cases of demand uncertainty, information asymmetry and moral hazard: (1) when retailers have private information about an uncertain state of the demand (Gal-Or, 1991); (2) both the upstream and downstream firms make a non-price choice (e.g. advertising, sales effort, etc.) subject to moral hazard – double or two-sided (Romano, 1994); and (3) when the manufacturer faces uncertain demand (Butz, 1997).

Iyer (1998) examines a channel with two symmetric retailers engaging in price and non-price competition (e.g. provision of product information, after-sales service etc.). Consumers are heterogeneous in their locations (as in the spatial models of horizontal differentiation) and in their willingness to pay for retail services (as in the models of vertical differentiation). When the diversity in willingness to pay is relatively greater than locational differentiation, neither quantity discounts nor a menu of two-part tariffs are sufficient to coordinate the channel. A complicated menu of contractual mechanisms is necessary that can induce retail differentiation so that all retailers don't compete only for consumers with low willingness to pay (by engaging in price competition) or only for consumers with high willingness to pay (by engaging in non-price competition). An example of such a menu is one consisting of retail price restraints linked to particular wholesale prices and fixed fees.

In general, RPM restricts the resellers' freedom to set prices. Minimum RPM can be anticompetitive by acting as a monitoring or an enforcing mechanism that facilitates collusion of an upstream or downstream cartel or by facilitating third-degree price discrimination by a monopolistic manufacturer (Gilligan, 1986). Although maximum RPM is traditionally viewed as reducing retail price,[6] it could reduce consumer welfare by reducing the number of retailers (Perry and Groff, 1985) or facilitate manufacturer opportunism, whereby it may drive prices down enough so that the retailers almost fail and then the manufacturer may exploit such retailers (Blair and Lafontaine, 1999). Hence both forms of RPM are viewed unfavorably by the US Supreme Court.

Since 1911, and until recently, either form of RPM was *per se* illegal under Section 1 of the Sherman Antitrust Act. This meant that a violation of Section 1 had been established once the government or private plaintiff proved that the defendant manufacturer had implemented an explicit or implicit plan to maintain a resale price. However, the last few years have seen legal cases where a price maintenance agreement between an upstream supplier and a downstream distributor is judged on its unique circumstances. In its *State Oil Company, Petitioner v. Barkat U. Khan and Khan & Associates, Inc.* decision of 1997, the Court returned the antitrust treatment of maximum RPM to the 'rule of reason', so that now a defendant manufacturer can defend itself by demonstrating that, in its case, maximum RPM has pro-competitive effects that benefit the consumers (Roszkowski,

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[5] On a different note, Perry and Porter (1990) show that minimum RPM can result in excessive retail service or induce new entry because of the reduced price competition.

[6] When the manufacturer can set both a franchise fee and a wholesale price, Perry and Besanko (1991) show that the traditional view that maximum RPM will lower retail prices and that minimum RPM will raise retail prices may be reversed.

1999). More recently, in June 2007, the Supreme Court's decision in *Leegin Creative Leather Products Inc. v. PSKS Inc.* established that courts should also evaluate minimum RPM according to the 'rule of reason'.[7]

4.4 Slotting allowances

Unlike fixed fees that retailers pay to manufacturers in two-part tariffs, slotting allowances are payments made by manufacturers to retailers. They include a wide assortment of fixed transfers from manufacturers to retailers that are not linked to quantities sold. These have been variously called pay-to-stay fees, failure fees, premium shelf-placement fees, share of shelf-space fees etc.

Sullivan (1997) argues that as the cost of developing new products falls, more new products are supplied; slotting allowances emerge as a means by which to ration shelf space efficiently to the most profitable products. Another argument often used is that when shelf space is a scarce resource, slotting allowances serve to shift the risk of failure from the retailers to the manufacturer. This risk-shifting becomes particularly important in the presence of private information about the success of the product in the hands of the manufacturer. Lariviere and Padmanabhan (1997) and Desai (2000) argue that slotting allowances are means by which manufacturers signal to retailers their private information about the quality of their products. Desai (2000) shows that slotting allowances can be pro-competitive as it serves to enhance retailer participation because it reduces the demand uncertainty of retailers and increases their profitability. But Shaffer (1991) argues that slotting allowances are anticompetitive because they reduce retail competition and increase prices.

While Shaffer assumes that manufacturers are in a perfectly competitive market and therefore have no power and the retailer sets the terms of trade, in Desai's model, the manufacturer sets the terms of trade. In both models, wholesale prices are higher in the presence of slotting allowances. But with manufacturers setting the terms of trade and using slotting allowances as a signaling device, the likelihood of slotting allowances falls when there is greater market potential (as understood by both manufacturers and retailers). This is because retailers find it worthwhile to participate in the market even without slotting allowances when the market is profitable. However, when the retailer seeks to exercise power, the retailer can extract the manufacturers' entire surplus through slotting allowances. Then slotting allowances should increase with market potential.[8]

In terms of empirical research, Bloom et al. (2000) and Wilkie et al. (2002) use surveys of manufacturers and retailers to identify key reasons why slotting allowances are used. However, the results are inconclusive because retailers and manufacturers have somewhat opposing views. Rao and Mahi (2003) survey manufacturers and retailers about each transaction they were involved in. They find that slotting allowances increase with greater retailer power, but acknowledge that the results may be due to their inability to control for manufacturer–retailer power at the level of each transaction due to pooling transactions across a wide range of manufacturers and retailers.

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[7] *Source*: Knowledge@Wharton, 08 August 2007.

[8] Chu (1992) develops a screening model where retailers use slotting allowances to screen new products for their potential. Again, with this model where the retailer has power, slotting allowances increase with the potential of the product.

Sudhir and Rao (2006) use a database of all new products offered to a particular retailer, some of which received slotting allowances and others that did not. By using such a universe of accepted and non-accepted products, they are able to control for any potential issues of selection involved in using only accepted products. They also had internal ratings data of retailer buyers on the potential for success. These data enabled them to study which of the rationales are supported in their data by sidestepping the common problems of selection and levels of information asymmetry for any new product. Broadly, Sudhir and Rao find support for the efficiency rationales: opportunity costs, information asymmetry, signaling and retail participation. They do not find support for the retail power and retail competition mitigation (with an anticompetitive rationale) hypotheses.

Israelevich (2004) shows evidence based on a policy analysis using a structural model that slotting allowances (pay to fees) serve to put products on retailer shelves that may not be profitable purely through the revenues they generate for the retailer; thus slotting allowances may serve to increase consumer variety. The question of whether other better products that could be more in demand by consumers are being pushed out from the shelves due to slotting fees is yet to be resolved.

Slotting allowances for existing products may also be given to enhance retailer participation in activities such as in-store service or merchandising. These allowances may be called display allowances or advertising allowances, and may fall under the broad rubric of slotting allowances. Kim and Staelin (1999) show that with greater store substitutability, manufacturers will 'freely' give retailers side payments to increase merchandising. If a retailer passes through a greater portion of these side payments to the consumer, then the manufacturer increases the side payment to this retailer. In addition, the competing retailers will react by lowering their retail margin and, thus, regular retail price. The authors present comparative static results for how changes in consumer sensitivity to pricing and promotional activities affect prices, side payments, and both retailer and manufacturer profits.

4.5 Future research

As we have seen, manufacturers might use any of the several possible pricing schemes or they could even use a combination of pricing schemes. Future research needs to address: (1) what are the implications of different pricing contracts for pass-through?; (2) how does retail competition, manufacturer competition and the overall channel structure influence the choice of pricing contract?; and (3) what combination of pricing schemes might be used under what market situations?

Different pricing schemes would have different implications for how pass-through is defined and measured. Specifically, when wholesale prices are not observed, the researcher should be wary that, with a nonlinear pricing scheme, the marginal cost could be different for different retailers. This could, in turn, result in different pass-through behaviors across competing retailers. Also, researchers should be cautious about using directly observed wholesale prices if, say, side payments or slotting allowances, which are not observed by the researcher, change the effective wholesale price for the retailer. Inferring pass-through behavior through a structural model that tests different hypotheses on the contracting and pricing relationships between manufacturers and retailers could be one potential solution.

It would be interesting to see if retailers' pass-through behavior might influence the pricing contract set by manufacturers. While the causality between the pricing contract

and the pass-through behavior may be difficult to tease out, it is nonetheless interesting to explore this issue. For instance, it is known that pass-through behavior changes between regular and peak demand periods. What terms might a manufacturer want to incorporate in the pricing contract (e.g. RPM) to guard itself against these variations? How might a manufacturer want to set the contract differently when retailers' objective is brand profit maximization versus when retailers' objective is category profit maximization?

Heterogeneity among retailers (Ingene and Parry, 2000), and the relative bargaining power of manufacturers and retailers (Iyer and Villas-Boas, 2003; Shaffer, 1991; Desai, 2000) have implications for the terms of the pricing contract. Different retail formats (supermarkets versus discount stores or club stores) carry an assortment of products and attract different kinds of consumers, and hence face very different demand structures. Hence the bargaining power of a retailer may not only depend on the extent of retail competition in the market but also on the store format. Future research should analyze pricing contracts in the context of differences in demand structures and bargaining power of competing retailer formats.[9]

Chen (2003) studies the situation where an upstream supplier uses two-part tariffs for its downstream retailers, which include a dominant retailer and competitive fringe retailers. The dominant retailer is more efficient at a large scale of operation (i.e. it has a cost advantage). In order to offset the reduction in profits caused by the rise in the dominant retailer's power, the manufacturer seeks to boost the fringe retailers' sales by lowering wholesale prices to them. This in turn leads to greater retail competition and lower prices. Dukes et al. (2006) consider a bilateral bargaining situation of competing manufacturers and competing multiproduct retailers. In this setting, manufacturers raise prices to the weaker retailer in order to boost sales through the more efficient retailer, which is also more profitable. This in turn reduces retailer competition and raises retail prices. Manufacturers' increased bargaining power over the weaker retailer allows them to accrue, in part, the additional extracted consumer surplus. These findings need to be empirically tested in view of their implications for pass-through behavior of dominant versus weak retailers, with and without manufacturer competition.

Both Chen (2003) and Dukes et al. (2006) assume that the manufacturers can charge different prices to the powerful and weak retailers, but, as pointed out earlier, manufacturers could instead use menu pricing schemes to overcome the limitations imposed by the Robinson–Patman Act. While the Robinson–Patman Act does not allow a manufacturer to discriminate between retailers, different manufacturers might offer different contracts to the same retailer. Hence, with regard to upstream competition, it would be interesting to understand when competing manufacturers might offer different pricing contracts or pricing schemes to their retailers. For example, would a national brand and a local brand always offer the same pricing scheme to a retailer? If not, then when might they differ?

Future research should investigate how different channel structures influence pricing contracts. For instance, as will be discussed in the next section, the presence of a direct channel that is owned by the manufacturer (a partially integrated channel) could strain

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[9] One source of retail power has been the emergence of store brands. We refer the reader to the companion chapter on store brands in this handbook for a survey of issues relating to store brands.

the manufacturer–retailer relationship. What is the optimal pricing contract under such a scenario? Also a distribution channel could evolve over time because of mergers or because manufacturers and retailers enter or exit the market. This would change the extent of competition upstream or downstream, and also the demand for individual retailers. How should the pricing contract be designed to adjust for such potential changes in the channel structure?

Iyer and Villas-Boas (2003) note that empirically the use of two-part tariffs is considerably small despite findings in the theoretical literature about the optimality of such tariffs. While bargaining between the channel members could be a possible reason, an alternate reason could be that the real-world settings are far more complex, and as the findings of Chen et al. (2001) and Iyer (1998) suggest, manufacturers might be using more complicated pricing schemes. Future research thus needs to incorporate more efficiently the characteristics of channel members, characteristics of the product and consumer behavior in analyzing the issue of setting a wholesale pricing contract, while allowing for the use of a combination of different pricing schemes.

5. Channel structure

The channel structure is a long-term decision where managers decide on the structure of the distribution channel given the market characteristics. Managers can decide whether to have an integrated channel (sell directly to the consumer) or a decentralized channel (use intermediaries such as retailers, dealers etc.) or a combination of both – a partially integrated channel (e.g. use a direct online channel and traditional retailers). For a channel with intermediaries, managers can not only decide the number of players at each level; they can also choose among different options such as exclusive dealers (EDs), exclusive territories (ETs) and independent profit-maximizing retailers. While making such a decision, managers need to take into account the optimal pricing strategy that can be implemented in the resulting channel structure, given the market characteristics (e.g. competition, demand uncertainty, power structure).

5.1 Vertical integration and decentralization

In the illustrative model of Section 2, we found that vertical integration (VI) can solve the double marginalization problem and the associated pricing inefficiency from an independent retailer (Jeuland and Shugan, 1983). VI can lower retail prices for other channel structures as well – upstream monopolists selling through multiple downstream monopolists (Romano, 1987), a duopoly channel structure with exclusive dealers (McGuire and Staelin, 1983; Coughlan, 1985), and a 'full channel' structure with two competing manufacturers both selling through both competing retailers (Trivedi, 1998).[10]

Although VI can internalize the double marginalization problem, when the retail market is highly competitive (as a result of, say, high product substitutability[11]), manufacturers may be better off if they can shield themselves from the competitive environment by inserting privately owned profit-maximizers (retailers) between themselves and the

[10] The integrated structure has two manufacturers selling directly to consumers.

[11] Product substitutability is defined as the ratio of the rate of change of quantity with respect to the competitor's price to the rate of change of quantity with respect to own price.

ultimate retail markets (McGuire and Staelin, 1983; Coughlan, 1985; Lin, 1988).[12] This is because marketing middlemen soften manufacturer competition as the effect of a price change by a manufacturer on final retail demand is weakened by the intermediary. Other channel restraints such as exclusive dealing (Trivedi, 1998) and exclusive territories (Rey and Stiglitz, 1995) can also reduce manufacturer competition.

Moorthy (1988) showed that retail competition is not necessary for decentralization to be a Nash equilibrium. What is critical is the nature of coupling between demand dependence and strategic dependence. The author shows that decentralization is a Nash equilibrium only if one of the following (mutually exclusive) conditions are satisfied: (1) the manufacturers' products are demand substitutes at the retail level and strategic complements at the manufacturer or retailer levels; (2) the manufacturers' products are demand complements at the retail level and strategic substitutes at the manufacturer or retailer levels.

In general, with pure price competition, a mixed channel structure where one firm vertically integrates while another decentralizes is not an equilibrium. However, when retailers engage in price and non-price competition (e.g. provision of product information, after-sales service etc.), Iyer (1998) shows that a mixed channel structure can be an equilibrium in markets with weak brand loyalty. Although the decentralized retailer will charge higher prices than those chosen by the vertically integrated firm, adopting a high-end service position helps the retailer to differentiate and support the higher price. Hence the corresponding manufacturer's incentive to decentralize is reinforced in equilibrium.

We have already mentioned that demand functional form and manufacturer–retailer interactions affect pass-through. Choi (1991) and Trivedi (1998) analyze the effect of demand functional forms and manufacturer relationship on channel structure. The two papers find a rich set of results on how channel structure decisions are affected by functional form and manufacturer–retailer interactions.

The channel structure may also evolve over time with the entry of new players into the market. Tyagi (1999b) shows demand conditions where, contrary to conventional wisdom, entry of a new downstream firm lowers the downstream market output and increases the consumer price. This is because the upstream firms gain bargaining power with downstream entry, raising their wholesale price, and this effect can overcome the competitive effect of entry. But he also shows that for a class of widely used demand functions – linear, constant elasticity and a variety of convex and concave demand functions – the supplier's optimal price is invariant to the entry/exit of downstream firms. Similarly, Corbett and Karmarkar (2001) model competition and entry into different levels of a multiple-tier serial channel structure with a price-sensitive linear deterministic demand and find that price per unit, in a tier, falls with the number of entrants in any upstream tier, but is unchanged with the number of entrants in a downstream tier.

Desai et al. (2004) discuss the role of the intermediary in the context of durable goods. There are two issues with durable goods: (1) the presence of secondary market competition; and (2) the Coase problem, where the manufacturer's inability to commit to a future price causes consumers to wait and the market to fail. Desai et al. show that by pre-committing the retailer to a two-part contract that covers both periods, the manufacturer can solve

[12] They all find conditions under which decentralization is a Nash equilibrium strategy of manufacturers.

both problems. With pre-committed wholesale prices, the channel can replicate the sales schedule under a consumer-pricing commitment. Interestingly, in this contract, the manufacturer charges a wholesale price above marginal cost in both periods and earns higher profits by selling through a retailer than by selling the product directly to the consumers.

5.2 Partial integration

Manufacturers may also consider partial integration (PI) – taking over part of the downstream industry – as a channel design strategy. The popular argument for this strategy is the manufacturer's incentive to raise rivals' (independent retailers') costs. Romano (1987) considers the case when an upstream monopolist services two downstream monopolists. Through PI, the upstream monopolist can not only (partially) eradicate the pricing inefficiency associated with successive monopolies, but also practice implicit price discrimination towards the non-integrated downstream firm. Hastings and Gilbert (2005) focus on the 1997 acquisition by Tosco of Unocol's West Coast refining and retail assets. They empirically examine the reaction of Tosco's wholesale prices in 13 metropolitan areas to differential increases in competition with independent retailers resulting from the merger. The upstream firms (refineries) have market power and the downstream products (gasoline from different refineries) are strategic complements. The authors find that an increase in the degree of integration is associated with higher wholesale prices to competing retailers.

The emergence of the Internet as a sales channel has brought the issue of partial forward integration into focus again in recent years. The growth of the Internet has made it very easy for manufacturers to directly connect with the final consumer through an online store (direct channel). While the direct channel reduces the manufacturer's dependence on retailers and eliminates pricing inefficiencies due to double marginalization, it is also likely to steal customers from retailers. This might strain the manufacturer–retailer relationship and may cause retailers to react in a way that adversely affects the manufacturer. It has been shown that firms can control the competition between the online channel and the traditional retailers by controlling the amount of information made available on the online channel (Balasubramanian, 1998; Zettelmeyer, 2000; Brynjolfsson and Smith, 2000).

The online channel, however, may not always be detrimental to the non-integrated retailers. Chiang et al. (2003) analyze the price-setting game between a direct channel of a manufacturer and its independent retailer. They find that, depending on consumers' acceptance of direct channel purchases (for low acceptance), the introduction of the direct channel may be accompanied by a wholesale price reduction (as a result of low direct channel prices).

Kumar and Ruan (2006) consider the case when a retailer carries products of competing manufacturers and maximizes category profits. Consumers in the market are one of two types – they are either brand loyal or store loyal. In addition to the retail price, the retailer is also allowed to set the level of merchandising support, which impacts the demand for the manufacturer's product. They find conditions under which a manufacturer may get higher margins from brand-loyal customers online, and then offer higher margins to the retailer to get better merchandising support and a greater share of the store-loyal consumers. Thus, under certain conditions, the online channel not only serves to increase the level of retail support and manufacturers' profits, but it may also increase retailers' profits.

5.3 Future research

The literature on channel structure in marketing has typically assumed that consumer demand is deterministic. However, the operations literature typically highlights the variability in consumer demand. Small levels of consumer demand variability are amplified across a channel and lead to the well-known 'bullwhip effect', and harm channel efficiency (Lee et al., 1997). Thus a decentralization decision may depend on demand variability, which is typically abstracted away from in the traditional channel structure literature in marketing. It is critical to understand the tradeoffs when designing channels in the presence of demand uncertainty, retailer/manufacturer moral hazard etc.

While there has been a large volume of theoretical research on issues of channel structure, the volume of empirical research on this issue has been very limited. This is partly because channel structure decisions tend to be long term and therefore researchers cannot get variation in the data. The emergence of the Internet has provided opportunities to study the effect of a change in channel structure, and empirical researchers should take advantage of this natural variation in the data.

6. Structural econometric models of pricing in a channel

In this section, we discuss the emerging literature on structural econometric models of channels. We begin by discussing an illustrative model. In recent years, a number of papers have used the structural econometric framework to model the marketing channel. Such models serve to (1) depict manufacturer–retailer interactions that best describe the market and (2) perform policy analysis in markets where a channel intermediary needs to be modeled. We discuss these two types of models in turn.

6.1 An illustrative structural econometric model of channels

We illustrate a basic structural econometric model of the channel using a logit demand model to highlight the key aspects of developing a structural econometric model of the marketing channel.

Demand Consider a market where households can choose between two brands (sold by two different manufacturers) denoted by $i = 1, 2$ and a no-purchase option denoted by $i = 0$. The utility for a brand i to household h in period t is given by

$$\begin{aligned} U_{hit} &= \beta_{0i} + X_{it}\beta - \alpha p_{it} + \xi_{it} + \varepsilon_{hit}, \quad i = 1, 2 \\ &= \delta_{it} + \varepsilon_{hit}, \quad i = 1, 2 \end{aligned} \tag{15.1}$$

where X_{it} is a vector of observable (to the firm and the econometrician) attributes and marketing variables (for, e.g., display and feature activity for the brand) and p_{it} is the retail price. β_{0i} is the intrinsic preference of consumers for brand i, and ξ_{it} is the unobservable (to the econometrician, but observable to the firm and the consumer) component of utility. This term captures the variation in consumer preferences for brands across time that is induced by manufacturer advertising and consumer promotions. ε_{hit} is household h's idiosyncratic component of utility which is unobserved by the firm and is assumed to be independent and identically distributed as a Type I extreme value distribution across consumers. This assumption leads us to the familiar multinomial logit model of demand. Denote the deterministic part of the utility that is observed by the firm by the term δ_{it} and,

normalizing the deterministic component of utility for no purchase (δ_{0t}) to zero, we have the familiar equation for market share for the brand

$$s_{it} = \frac{\exp(\delta_{it})}{1 + \sum_{k=1}^{2} \exp(\delta_{kt})}, \quad i = 0, 1, 2 \tag{15.2}$$

It is therefore easy to see that

$$\ln(s_{it}/s_{0t}) = \delta_{it} = \beta_{0i} + X_{it}\beta - \alpha p_{it} + \xi_{it}, \quad i = 1, 2$$

This equation serves as the demand-side estimation equation. The term ξ_{it} serves as the error term in the estimation equation. It can capture the effects of manufacturer advertising and consumer promotions, and other unobserved demand shocks that are not explicitly modeled.

The supply (or channel) model

Assume that the two manufacturers set wholesale prices and the retailer then sets retail prices to maximize its category profits in period t. Then the retailer's objective function is given by

$$\Pi^{R_t} = (p_{1t} - w_{1t})s_{1t}M_t + (p_{2t} - w_{2t})s_{2t}M_t$$

where p_{1t} and p_{2t} are the retail prices of products 1 and 2, w_{1t} and w_{2t} are the wholesale prices of products 1 and 2 set by the manufacturers, and s_{1t} and s_{2t} are the shares of products 1 and 2 defined in the demand model (note that $s_{0t} = 1 - s_{1t} - s_{2t}$ is the share of the outside good) and M_t is the size of the market. The t subscript refers to the period t.

The first-order conditions for the retailer are given by

$$\frac{\partial \Pi^{R_t}}{\partial p_{it}} = s_{it} + (p_{1t} - w_{1t})\left[\frac{\partial s_{1t}}{\partial p_{it}}\right] + (p_{2t} - w_{2t})\left[\frac{\partial s_{2t}}{\partial p_{it}}\right] = 0, \quad i = 1, 2$$

Taking the derivatives of market share with respect to prices, we have

$$\frac{\partial s_t}{\partial p_t} = \begin{pmatrix} \frac{\partial s_{1t}}{\partial p_{1t}} & \frac{\partial s_{2t}}{\partial p_{1t}} \\ \frac{\partial s_{1t}}{\partial p_{2t}} & \frac{\partial s_{2t}}{\partial p_{2t}} \end{pmatrix} = \alpha \begin{pmatrix} -s_{1t}(1 - s_{1t}) & s_{1t}s_{2t} \\ s_{1t}s_{2t} & -s_{2t}(1 - s_{2t}) \end{pmatrix} \tag{15.3}$$

Solving the first-order conditions, we get the formula for retail prices that is written in matrix form.

$$p_t = w_t + \frac{1}{\alpha(1 - s_{1t} - s_{2t})} \text{ where } p_t = \begin{pmatrix} p_{1t} \\ p_{2t} \end{pmatrix} \text{ and } w_t = \begin{pmatrix} w_{1t} \\ w_{2t} \end{pmatrix} \tag{15.4}$$

If the wholesale prices can be observed, the equation above can serve as the supply side equation for the retailer. One could potentially capture unobservable retailer costs as an error on the supply equation.

Alternatively one may wish to actually write out an equation to describe the wholesale

prices in order to structurally model the wholesale price choices. In that case, one will write out the manufacturers' pricing model. To illustrate different types of manufacturer pricing behavior, consider the two alternatives of (1) tacit collusion and (2) Bertrand competition. The objective function of manufacturer i selling brand i in period t is given by

$$\Pi^{M_{it}} = (w_{it} - c_{it})s_{it}M_t + \theta(w_{jt} - c_{jt})s_{jt}M_t - F_{it}, \quad i = 1, 2; j \neq i$$

where w_{it} is the wholesale price for brand i that the manufacturer charges the retailer and c_{it} is the marginal cost of brand i. F_{it} is the fixed cost to the manufacturer (it can include costs that are not related to the marginal sales of the brand, for, e.g., slotting allowances). Note that $\theta = 1$ for the case of tacit collusion and $\theta = 0$ for the case of Bertrand competition. Let the marginal cost of brand i be $c_{it} = \gamma_i + \omega_{it}$, where γ_i is the brand-specific marginal cost, and ω_{it} is the brand-specific unobservable marginal cost at time t. Note that ω_{it} is unobservable to the researcher, but observable to the manufacturers.

The first-order conditions for the manufacturer are given by

$$\begin{aligned} \frac{\partial \Pi_{it}^M}{\partial w_{it}} &= s_{it} + (w_{it} - c_{it})\left[\frac{\partial s_{it}}{\partial p_{1t}}\frac{\partial p_{1t}}{\partial w_{it}} + \frac{\partial s_{it}}{\partial p_{2t}}\frac{\partial p_{2t}}{\partial w_{it}}\right] + \\ &\quad \theta(w_{jt} - c_{jt})\left[\frac{\partial s_{jt}}{\partial p_{1t}}\frac{\partial p_{1t}}{\partial w_{it}} + \frac{\partial s_{jt}}{\partial p_{2t}}\frac{\partial p_{2t}}{\partial w_{it}}\right] = 0, \qquad i = 1, 2; j \neq i \\ s_t &+ \left[\left(\frac{\partial p_t}{\partial w_t}\frac{\partial s_t}{\partial p_t}\right).*\Theta\right](w_t - c_t) = 0 \end{aligned}$$

where

$\Theta = \begin{pmatrix} 1 & 1 \\ 1 & 1 \end{pmatrix}$ for tacit collusion and $\Theta = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$ for Bertrand competition. The .* operator denotes element by element multiplication of a matrix.

We can thus solve for the wholesale prices as

$$w_t = c_t + \left[\left(-\frac{\partial p_t}{\partial w_t}\frac{\partial s_t}{\partial p_t}\right).*\Theta\right]^{-1} s_t \tag{15.5}$$

where the term in brackets after c_t is the vector of margins that manufacturers choose for their brands. The retailer's reactions to manufacturers' wholesale prices are obtained by taking the derivatives of the retail prices in (15.4). It can be shown that (see Sudhir, 2001 for the proof)

$$\frac{\partial p_t}{\partial w_t} = \begin{pmatrix} \frac{\partial p_{1t}}{\partial w_{1t}} & \frac{\partial p_{2t}}{\partial w_{1t}} \\ \frac{\partial p_{1t}}{\partial w_{2t}} & \frac{\partial p_{2t}}{\partial w_{2t}} \end{pmatrix} = \begin{pmatrix} 1 - s_{1t} & -s_{1t} \\ -s_{2t} & 1 - s_{2t} \end{pmatrix}$$

If we observe wholesale prices and retailer prices, we can model the supply side by fitting both equations. However, typically, wholesale prices are not observed and most

researchers in marketing substitute the wholesale price equation into the retail pricing equation and fit the following retailer pricing equation to the data:

$$p_t = \underbrace{\underbrace{c_t}_{\text{Manufacturer cost}} + \underbrace{\left[\left(-\frac{\partial p_t}{\partial w_t}\frac{\partial s_t}{\partial p_t}\right).*\Theta\right]^{-1} s_t}_{\text{Wholesale margin}}}_{\text{Wholesale price } (w_t)} + \underbrace{\frac{1}{\alpha(1 - s_{1t} - s_{2t})}}_{\text{Retail margin}} \tag{15.6}$$

There are some key aspects that should be highlighted in the derivation of the structural econometrics models. First the demand-side error is incorporated into the supply-side equations through the observed market shares. Note that, in contrast to the game-theoretic models of Section 2.1, where the retailer and wholesale pricing equations are characterized completely in terms of the primitive demand and cost parameters, the pricing equations here (15.4 and 15.5) are characterized in terms of the observable market shares. The advantage of incorporating observed market shares is that demand-side errors (which are observable to the consumers and firms) are allowed to affect prices. In this sense, the structural econometric specification acknowledges that econometric errors have structural meaning and are accounted for in the specification.

In summary, a standard structural econometric model of channels is a simultaneous equation model with demand and supply pricing equations (could be one equation for manufacturer and retailer each or combined into one), both specified in terms of behavioral primitives. The demand equation relates quantity purchased to retail price, product characteristics and unobserved demand determinants. While many types of demand models can be used, the random coefficients logit model remains the most popular because of its flexibility in capturing substitution patterns, while still providing closed-form solutions that do not require integration for individual-level choice probabilities (see Dubé et al., 2002 for discussion). The supply equation relates prices to a markup and to observed and unobserved cost determinants. The structural econometric model can be used to either infer the consumers' and firms' decision rules from observable retail price–quantity pairs, or to perform policy simulations on how the equilibrium will evolve in response to actions by firms.

6.2 Descriptive models of channels

Sudhir (2001) demonstrated how to construct a structural econometric model of the channel under alternative assumptions of manufacturer–retailer interaction. In his analysis of competition among manufacturers selling through a single retailer, he finds that the manufacturer Stackelberg model of vertical interactions fits the data better than the vertical Nash model. He also finds that the category profit maximization objectives fit the data better than brand profit maximization objectives. He finds that the logit model fits the data better than a constant elasticity multiplicative model of demand, suggesting that even though multiplicative models fit the data well, they are less useful in retail decision support systems, because the implied markups are less consistent with the data.

Berto Villas-Boas (2007) expands the analysis to vertical interactions between multiple manufacturers and multiple retailers using a general random coefficients logit model. She finds that wholesale prices are close to marginal cost, but retailers have pricing power in the market. This could be consistent with either retail power or nonlinear pricing contracts. Bonnet and Dubois (2008) explicitly model nonlinear contracts involving two-part tariffs and resale price maintenance, and find that manufacturers use two-part tariffs with RPM.[13] Unlike Berto Villas Boas, they find that retailers price at marginal cost.

Berto Villas-Boas, and Bonnet and Dubois do not observe wholesale prices. Using a conjectural variations framework, Kadiyali et al. (2000) take advantage of the fact that wholesale prices can be observed in their data and estimate the extent of channel power. Their findings suggest that channel participants deviate from the prices predicted by 'standard' games such as manufacturer–retailer Stackelberg and vertical Nash, and retailers have power in that they obtain the larger share of channel profits. While this is consistent with a two-part tariff, they find that neither manufacturers nor retailers charge zero markups. Similar to Kadiyali et al., Meza and Sudhir (2007) estimate both a retail and wholesale price equation, but explicitly look for departures from the short-term profit-maximizing prices predicted by the standard models. They find that retailers strategically deviate from short-term profit-maximizing retail prices to support their store brands, but manufacturer margins are consistent with a manufacturer-Stackelberg model. Again both manufacturers and retailers have non-zero markups.

There appears to be a discrepancy in extant research: when wholesale prices are observed, Kadiyali et al. and Meza and Sudhir observe positive markups by manufacturers and retailers; when wholesale prices are not observed, Berto Villas-Boas and Bonnet and Dubois find evidence of zero markup for either manufacturer or retailer. While the differences may be artifacts of the specific markets studied, the differences in inference of markups when wholesale prices are not observed should be explored systematically in future work.

In contrast to the above analysis using aggregate data, Villas-Boas and Zhao (2005) use household-level data in a particular local market to evaluate the degree of manufacturer competition, retailer–manufacturer interactions, and retailer product category pricing in the ketchup market in a certain city using household level data. Che et al. (2007) also use individual data to model manufacturer and retailer behavior in the presence of consumer state dependence. Given the dynamics involved, they study the extent to which firms are forward looking in their pricing behavior. They find that firms are boundedly rational in that they look only one period ahead when setting prices.

6.3 Policy analysis within a channel setting

Several papers have also applied the structural econometric framework of channels in performing policy simulations on a wide range of marketing mix questions. These analyses have addressed product, pricing, promotions and channel issues.

Goldfarb et al. (forthcoming) use the structural econometric channel framework to measured brand equity. They estimate a demand model and then assess how prices and profits will change within a competitive setting in the presence of a channel when a brand

[13] They study the market for bottled water in France.

loses its intangible equity (as represented by the relative value of the intercept with respect to a base brand such as the store brand).

Israelevich (2004) addresses the issue of product variety and the role of slotting fees within a distribution channel. As discussed earlier, he finds that slotting fees have served to enhance the available product variety at a retailer, because the policy analysis indicates that retailers do not find all products to be intrinsically profitable. This result, suggesting two-part tariffs, where manufacturers are offering retailers allowances, is different from the pricing strategies suggested in the analysis of Berto Villas-Boas and Bonnet and Dubois. Clearly more research on the types of pricing contracts used for different types of products is required.

Besanko et al. (2003) study optimal targeted pricing on the part of manufacturers in the presence of retailers, using aggregate data within a competitive setting. Pancras and Sudhir (2007) study the optimal marketing strategies of a customer data intermediary, which needs to consider the value of its target pricing services to manufacturers in the presence of a retailer who sets retail prices. Hartmann and Nair (2007) estimate a demand system for tied good (razors and razor blades) when consumers shop across stores with different retail formats. Consumers buy razors disproportionately at grocery and drug stores, but the razor blades at club stores. As cross-elasticities between the two products are moderated by the retail channel, a policy analysis requires modeling the retail channel behavior. Chu et al. (2007) study the pricing behavior in the PC market and are able to assess the value of different distribution channels. They perform a variety of policy analyses on how dropping a distribution channel will affect firms. They also investigate the effect of the HP–Compaq merger using their estimates.

6.4 Future research

In summary, the structural models of channels literature has been able to map game-theoretic models to the data to both provide descriptions of the equilibrium interactions in the market, and perform policy analysis. As we pointed out earlier, there are some discrepancies in the inferences of power within the channel, depending on whether wholesale prices are observed or not. Further, there has been limited research on describing channel behavior in the presence of nonlinear contracts, because fixed transfers are typically not observed. More empirical research is needed in describing channel behavior in such markets.

While much extant research has focused on pricing as the key variable, future research should address other strategic variables such as manufacturer advertising and push versus pull promotions. Also current methodologies can deal with continuous strategic variables such as price, but new methodologies need to endogenize discrete decisions such as the retailer's decision to carry a product, introduce a new store brand etc. This would be in contrast to Israelevich's model, where he takes product acceptance decisions as exogenous. Such models can shed additional light on aspects such as how pricing contracts such as slotting allowances and trade deals affect product attractiveness and the decision to carry the product. Such advances not only require modeling advances, but also additional data on retailer product acceptance and rejection decisions (e.g. Sudhir and Rao, 2006) that would help us to learn about market behavior.

Far more challenging would be to model asymmetric information among channel members and how this may affect pricing contracts within a channel. This would require

us to have access to a variety of contracts entered into by a firm at alternative levels of information asymmetry. Such data, however, are hard to obtain. But detailed data from a particular retailer (manufacturer) about the pricing contracts it enters with different manufacturers (retailers) can be very useful in developing appropriate methodologies and obtaining insights into how channel members arrive at pricing contracts.

Overall, the ratio of empirical to theoretical research on pricing across channels is low. This situation is being remedied as more data on both consumer choices across channels and retailer pricing become available and new empirical tools for analyzing retailer behavior are being developed. We hope these tools will provide greater insights into consumer behavior across channels, channel structure and relationships, and the behavior of channel participants in the near future.

7. Conclusion

This chapter surveyed the analytical and structural econometric literature on pricing in a channel. We described the analytical literature on channels in terms of the time horizons of decision-making: pass-through, pricing contracts and channel structure. We described the econometric literature in terms of its two major applications: description and policy analysis. The chapter also discussed gaps in the literature in each of the areas, and offered suggestions for future research.

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16 Nonlinear pricing

Raghuram Iyengar and Sunil Gupta

Abstract

A nonlinear pricing schedule refers to any pricing structure where the total charges payable by customers are not proportional to the quantity of their consumed services. We begin the chapter with a discussion of the broad applicability of nonlinear pricing schemes. We note that the primary factor for the use of such schemes is the heterogeneity of the customer base. Such heterogeneity of preferences leads customers to choose different pricing plans based on their expected demand. We describe past analytical and empirical research. Past analytical work is categorized based on whether it is in a monopoly setting or a more general oligopoly context. Most past research has found two-part tariffs to be optimal in many settings. More recent research has begun to investigate the limits of such optimality and when a more general pricing scheme can be optimal. In the summary of empirical research on multi-part tariffs, we note that while nonlinear pricing schemes are popular, any analysis of demand under such schemes is nontrivial. One important reason is the two-way relationship between price and consumption in multi-part tariffs – the pricing scheme influences consumption and the level of consumption determines the applicable per-unit price. We describe how researchers have addressed this and other such issues and then show a modeling framework that integrates all the issues. We end by discussing empirical generalizations, which also suggest some promising areas for future research.

1. Introduction

A nonlinear pricing schedule refers to any pricing structure where the total charges payable by customers are not proportional to the quantity of their consumed services. The most common form is quantity discount for the purchase of large volumes. Several other forms of such pricing schemes exist across different industries. The following examples show the ubiquitous nature of this pricing strategy.

1. *Telecommunications* Most long-distance providers charge customers based on a combination of fixed fees (for access to the service) and per-minute price for each minute of a long-distance call. Wireless companies also charge customers in a similar manner for consumption of minutes but typically include some free minutes of consumption, along with a service plan.
2. *Consumer packaged goods* Quantity discounts are common in the consumer packaged goods industry. Typically, the per-unit price declines with package size. For instance, a recent search on Netgrocer.com showed that an 8 oz can of original B & M baked beans cost $1.39, which translates to $0.17/oz. A 16 oz can of the same baked beans cost $2.19, which is $0.14/oz. Some past research such as Nason and Della Bitta (1983) shows that consumers expect such quantity discounts.
3. *Electricity and water supply* Utility companies also offer quantity discounts. For instance, higher levels of consumption cost less for each kilowatt of consumption. In addition, energy rates for business users are different from those for residential users. Business users also incur varying rates based on peak versus off-peak electricity consumption.

4. *Business-to-business transactions* Many businesses offer quantity discounts to their customers. For instance in the electricity industry, customers purchasing large quantities of power have a high utilization as well. A quantity discount acknowledges the lower cost of idle capacity for such customers. Similar instances occur in the newspaper advertising industry, where businesses that advertise with a high frequency get charged at a lower rate per advertisement. See Dolan (1987) for a detailed discussion of various aspects of quantity discounts.
5. *Magazine subscriptions* Most magazines offer a lower rate for a two- or three-year subscription compared to the one-year subscription rate.

These examples show that nonlinear pricing takes many different forms. The purpose of this chapter is to summarize the research on nonlinear pricing. In Section 2, we explain the different kinds of nonlinear pricing schemes and discuss why such pricing schemes are used. Section 3 discusses the relevant managerial decisions for implementing such schemes. This is followed by a discussion in Section 4 on the theoretical findings on nonlinear pricing. In Section 5, we focus on empirical studies. Section 6 concludes the chapter.

2. Nonlinear pricing schemes – applications and motivation

Nonlinear pricing can be broadly classified in two categories – increasing block and decreasing block. In an increasing block pricing scheme, the marginal (per-unit) prices increase with quantity, whereas in a decreasing block scheme the marginal prices decrease with quantity. Figure 16.1 shows a few examples of increasing and decreasing block tariffs.

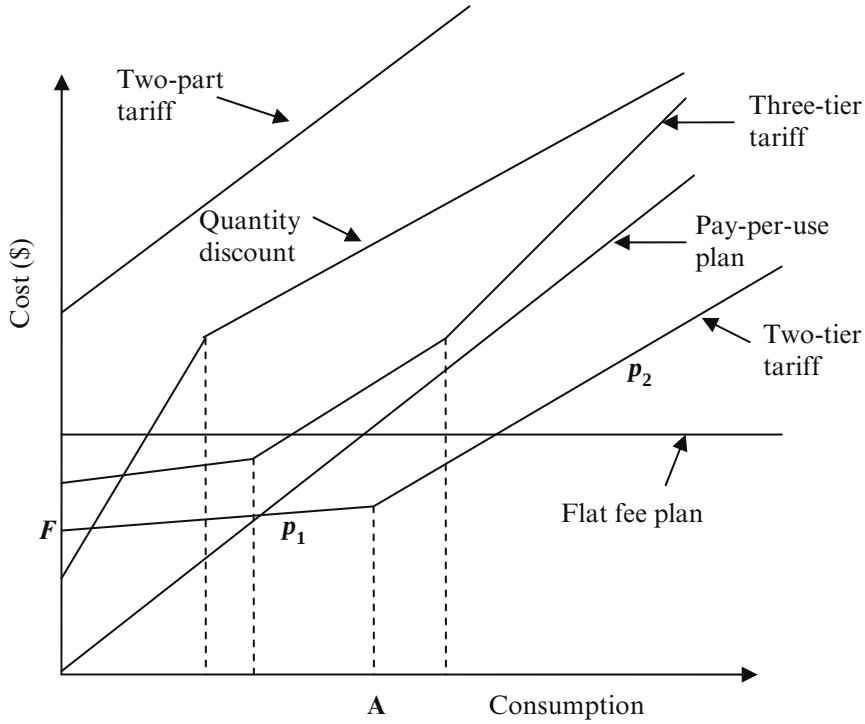
An increasing block tariff promotes conservation by penalizing excess consumption of units. A recent application of a multi-tier increasing block tariff for conservation is the electricity tariff in California. After the financial crisis in 2001, the California Public Utilities Commission imposed a new five-tier increasing block structure (see Reiss and White, 2005, p. 875 for more details). The new pricing scheme was implemented to encourage energy conservation. It was also expected to raise supplementary revenue for the state. Some evidence suggests that there was indeed a significant reduction in electricity consumption in 2001 as compared to the year before (Goldman et al., 2002).

A typical example of a decreasing block tariff is a quantity discount. For instance, Table 16.1 shows the rates that the *New York Times* charges in various categories (NYTimes Advertising Rates, 2008). Note that the rates decrease as the frequency of advertisement increases. This is essentially a mechanism for price discrimination – the advertisers who will commit to placing ads several times a year will get a cheaper rate than those customers who place only a one-time ad.

2.1 Reasons for nonlinear pricing

There are several reasons for firms to adopt a nonlinear pricing scheme. Here we discuss a few of the salient ones. See Wilson (1993) for a more detailed discussion.

1. *Price discrimination* Heterogeneity among customers is the primary reason to implement a nonlinear pricing scheme. This pricing structure can be thought of as a menu of quantities and corresponding charges. Each customer is expected to self-select the quantity–charge combination that is most appealing to him. As there is demand heterogeneity among customers, customers buy their ideal total quantity



Note: In the figure, the intercept on the vertical axis is the fixed fee associated with a pricing scheme while the slopes are the per-unit (marginal) prices. For the two-tier tariff, F refers to the access fee, p_1 and p_2 are per-unit (marginal) prices and A is the kink point when the per-unit price changes from p_1 to p_2.

Figure 16.1 Examples of nonlinear pricing schemes

Table 16.1 Advertising rates in the New York Times *for different categories*

Frequency (times/year)	Line rates ($)		
	Computer Services	Healthy Living	Home/Garden Guide
13	37.00	38.00	37.25
26	36.50	35.25	36.75
52	34.75	34.75	36.25

Source: *New York Times* website. See http://www.nytadvertising.com/was/ATWWeb/ProcessorAction.do.

based on how the per-unit rates vary with each incremental unit. Table 16.2 shows the wireless service plans offered by Verizon in the Philadelphia region. Note that these plans are an example of a two-tier (or three-part) tariff scheme.

Table 16.2 shows that there is significant variation in the number of free minutes among plans and thus can appeal to a wide customer base. In addition, plans are designed to offer a quantity discount to heavy users.

Table 16.2 Verizon wireless plans within Philadelphia, PA

Plans	Monthly access fee ($)	Overage rate ($/min)	Free minutes per month
1	39.99	0.45	450
2	59.99	0.40	900
3	79.99	0.35	1350
4	99.99	0.25	2000
5	149.99	0.25	4000
6	199.99	0.20	6000

Source: Verizon wireless website. See www.verizonwireless.com.

2. *Cost considerations* Decreasing block pricing schemes such as quantity discounts offer incentives for customers to stockpile and transfer the inventory of units from the firm to the customer. If the inventory cost for a firm is high, then such discounts offer a way of reducing its costs. Wilson (1993, pp. 15–16) gives an example from the electric utilities industry. In that industry, customers purchasing large quantities of power have a high utilization as well. A quantity discount acknowledges the lower cost of idle capacity for such customers.

   The pricing scheme within the package delivery industry provides another illustration of where the pricing scheme reflects cost considerations. Federal Express charges different rates depending on the weight of package and speed of delivery. Figure 16.2 shows the shipping charges for delivering a package from San Francisco to New York. These shipping charges increase with the weight of the package and the speed of delivery.
3. *Competitive pressures* Competitive pressures lead firms to use innovative nonlinear pricing schemes to entice customers. For instance, frequent flier miles began with each airline trying to acquire and retain business customers. Similarly, in the package delivery industry, many competitors of Federal Express such as UPS offer competitive nonlinear pricing schemes to draw customers. Figure 16.3 shows the package delivery charges from UPS for the same route (i.e. from San Francisco to New York).

A comparison of the UPS and Federal Express rates shows that they are similar, although the latter's prices are marginally lower. It is interesting to note that Federal Express also offers more alternatives – this can help customers to discriminate between companies even more. This suggests that the optimal design of a portfolio of nonlinear pricing plans involves the choice of number of plans as well as the pricing scheme for each plan.

3. Managerial decisions

The following example from long-distance telecommunications will provide a concrete context for the relevant decisions that a manager needs to make to set up a nonlinear pricing scheme.

Long-distance service providers typically price calling plans using a combination of

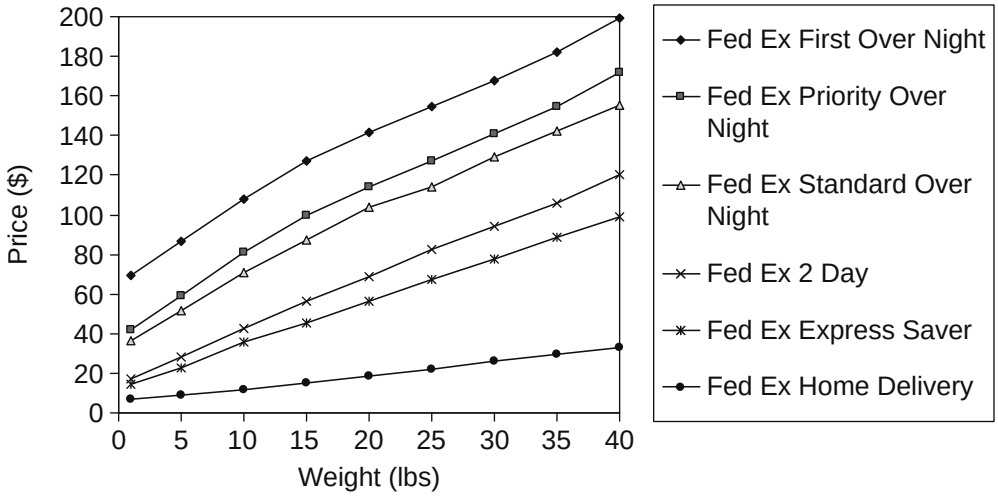


Figure 16.2 Federal Express delivery charges for shipping a package from San Francisco to New York

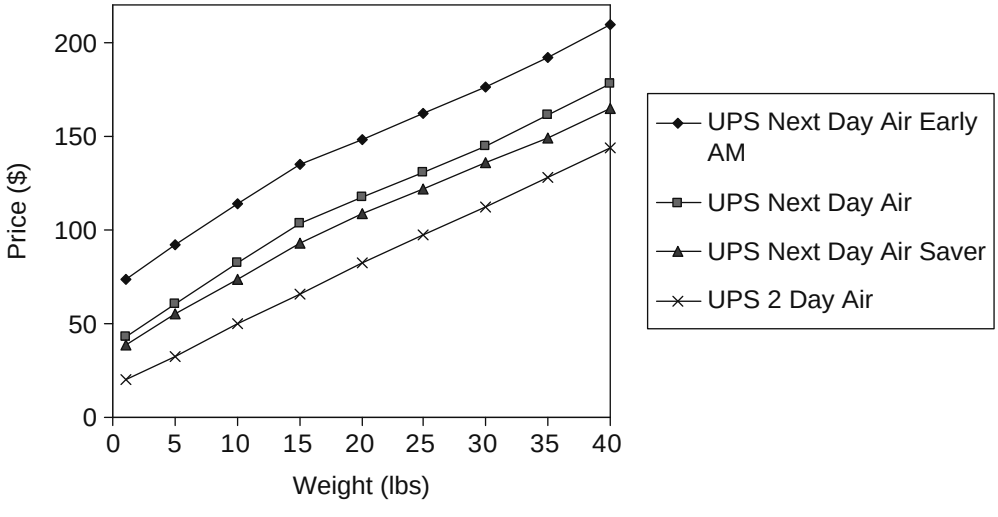


Figure 16.3 UPS delivery charges for shipping a package from San Francisco to New York

fixed fees (for access to the service) and per-minute price for each minute of a long-distance call. For instance, within New York State, Verizon offers several different callings plans. Table 6.3 illustrates these long-distance calling plans.

The table shows that there is some variation among the offered plans. For instance, the Timeless Plan has a fixed fee of $2.00 per month and a 10 c/minute rate for any consumption of long-distance minutes. This type of plan is termed a 'two-part tariff', with

Table 16.3 Verizon long-distance plans for New York State

Plan	Type of pricing plan	Monthly fee ($)	Detail of per-minute pricing
Timeless Plan	Two-part tariff	2.00	State-to-state and in-state calls: 10c/minute
E-Values	Two-part tariff	2.50	State-to-state and in-state calls: 10c/minute weekdays 7c/minute weekends
TalkTime 30	Three-part tariff	5.00	First 30 minutes free. Unused minutes do not carry over. State-to-state and in-state calls: 10c/minute after 30 minutes.
Verizon Five Cents Package Plan	Two-part tariff	6.00	State-to-state calls: 5c/minute In-state calls: 7c /minute
Verizon Freedom Value	Flat fee plan	34.99–39.99	Free

Source: Verizon website. See http://www22.verizon.com/Residential/Phone/Long+Distance/Long+Distance.htm.

the access fee and the per-minute price forming the two parts. Both Verizon Five Cents and E-Values have a similar structure but charge different prices for in-state and state-to-state calls. The remaining two plans (TalkTime 30 and Verizon Freedom Value) have a slightly different structure.

The Verizon Freedom Value Plan has an access fee ($34.99–$39.99) and any usage of long-distance minutes is free. Such type of plan is termed a 'flat fee' plan. Finally, the TalkTime 30 has three distinct components – an access fee ($5.00), per-minute rate (10 c/minute) and free minutes (30 minutes). Such a tariff is termed a 'three-part tariff'. Another popular term for this pricing scheme is a 'two-tier increasing block' tariff. Here, the term two-tier refers to the fact that there are two consumption regions based on different per-minute prices – region 1, when the consumption is less than 30 minutes, has a zero per-minute price and region 2, when the consumption is greater than 30 minutes, has a per-minute price of 10 c/minute. The term 'increasing block' signifies that the per-minute price in region 2 (10 c/minute) is greater than the per-minute price in region 1 (0 c/minute). Readers can immediately see that a two-tier increasing block tariff can be extended to a pricing scheme that has multiple tiers, which can be either increasing or decreasing block.

This example shows that nonlinear pricing schemes appear in many different forms – at one extreme, there is the special case of a flat fee plan and, on the other, there are multi-tier tariffs. Such a wide spectrum of plans can enable Verizon to appeal to different types of customers. When the pricing scheme involves a flat fee or in case of a two-part tariff, a relatively higher monthly access fee combined with a lower per-minute charge, heavy users are more likely to sign up for that plan. In contrast, light users will prefer the pricing scheme that has a relatively lower monthly access fee but a higher per-minute charge. This example also highlights the key managerial questions that have to be answered prior to designing a nonlinear pricing scheme. We show these decisions in Figure 16.4. There are three broad sets of decisions:

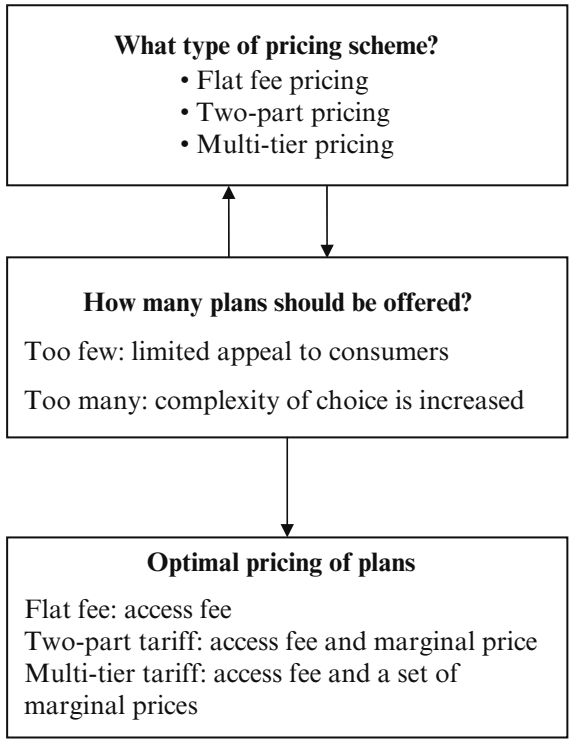


Figure 16.4 Managerial questions for implementing a nonlinear pricing scheme

1. *Type of pricing schemes* A typical portfolio of plans can have a flat fee, two-part tariff and even a few multi-tier tariffs. Much analytical work has investigated the optimality of two-part tariffs (Schmalensee, 1981; Stole, 1995; Armstrong and Vickers, 2001; Rochet and Stole, 2002). Are such two-part tariffs optimal in every circumstance or does the presence of competition and customer heterogeneity affect the optimality of a pricing scheme? Similar questions can be asked about multi-part tariffs.
2. *Number of plans* One of the primary motivations of nonlinear pricing is consumer heterogeneity, and thus offering too few plans limits its appeal to a wide range of customers. At the same time, past research suggests that increasing the number of plans might not be the answer either (Iyengar and Lepper, 2000; Iyengar et al., 2004). This line of work suggests that consumers are less motivated to make a decision if there are too many alternatives. The optimal number of plans, which would differ from one context to another, will then emerge from modeling the tradeoff between a firm's desire to offer many alternatives to appeal to the heterogeneous customer base and consumers' motivation to process all the information. In addition, as Figure 16.4 shows, the two decisions, i.e. the number of plans and type of pricing scheme for each plan, are interlinked.
3. *Optimal pricing of plans* Given a set of plans, a firm has to choose the access fees and marginal prices for each of these plans. These decisions have to consider the impact

of pricing structure on consumers' choice, consumption and retention. The presence of competition (see the earlier example of Fed Ex© and UPS©) can further complicate the situation.

Next, we discuss an example that shows how a firm designed a nonlinear pricing scheme.

3.1 Illustrative Example Deutsche Bahn AG

We discuss how Deutsche Bahn AG, the German railroad corporation, implemented a two-part tariff pricing scheme and also highlight the type of data collection and analysis required for designing such a scheme. This example is adapted from Dolan and Simon (1996, p. 164), where it is discussed in much greater detail.

Duetsche Bahn AG faced stiff competition from the automobile industry. It charged DM 0.36 per kilometer for first-class rail travel and DM 0.24 per kilometer for second-class travel. Compared to these prices, the typical gasoline price in Germany was about DM 0.15 per kilometer. Thus it was cheaper for everyone to drive and indeed most people did perceive the prices for rail travel to be too high. In addition, the company also did not price-discriminate in any other way among its customers. For instance, an obvious price segmentation strategy is based on frequency of travel, with heavy and light users being charged at a different rate. It is the possibility of implementing such usage-based price discrimination that led to the concept of BahnCard – a card that would have an annual fee and, once purchased, would lead to discounted trips. Such a pricing scheme is a two-part tariff as there is a fixed fee for access to the card and then a per-kilometer charge for any travel. Further, the two-part tariff scheme of the card would be designed such that it can be a viable alternative to attract people away from just driving to their destination. Intuitively, it would be the heavy users who will be drawn towards such a card.

On route to designing the pricing plan, the management of the railroad corporation struggled with several key questions:

(a) What percentage discount over the regular per-kilometer rate should be granted to BahnCard buyers?
(b) What should be the price of the BahnCard?
(c) How should the price be varied by class and special groups such as elderly and students?

The answers to these questions were critical to optimally designing the pricing plan and required extensive data collection from customers and potential customers of the railroad system. This data collection, in the form of responses to a conjoint design, measured the willingness to pay for varying levels of discounts. In addition, a model was developed to simulate the effects of the different pricing structures on customer segments and thereafter to estimate optimal pricing. This model took into account various tradeoffs, such as that a low price for the card may sell a high volume but the overall revenue may be negative as otherwise the full-paying heavy usage segment will pay a lower price. On the other hand, a high price for access to the card will deter many potential customers and even current customers might not increase their usage.

The analysis resulted in the set of optimal prices for both the fixed fee (access to the card) and the marginal price (percentage discount per kilometer) of the two-part tariff. The discount was set at 50 percent, i.e. the per-kilometer rate for first-class travel was DM 0.18 and for second-class travel, at DM 0.12. The fixed fee for the BahnCard for first- (second-) class travel was determined to be DM 440 (220). Finally, for elderly and the students, the card was offered at half the regular price.

We can analyze the attractiveness of this pricing scheme from the viewpoint of a second-class traveler. If the customer purchases a BahnCard, then he pays an initial fee of DM 220 and receives a rate of DM 0.12 per kilometer. Thus, for the first 100 kilometers, the customer pays a total of DM 232 (= DM 220 + 0.12*100). This translates to a rate of DM 2.32 per kilometer. If the customer did not purchase a BahnCard, he would be charged at the uniform rate of DM 0.24 per kilometer. At this rate, for the first 100 kilometers, he would pay only DM 24. The break-even point between paying the uniform rate and buying the BahnCard, and getting the discount rate occurs at around 1833 kilometers. If the customer is going to travel more than 1833 km annually, then it would be cheaper for him to purchase the BahnCard. Next, we compare the cost for a BahnCard customer with his cost for driving to his destination. As mentioned before, the typical gasoline charge was about DM 0.15 per kilometer. In this case, if the customer does not buy the BahnCard, then it would never be economical to travel by train. However, after purchasing the BahnCard, he receives a discounted per-kilometer rate that is lower than the per-kilometer rate for driving. The break-even point between driving and train travel occurs around 7333 km. If the customer is going to travel more than 7333 km annually, then it will cheaper for him to purchase the BahnCard.

Since its introduction in 1993, BahnCard has been a spectacular success. In 2004, there were about 3.2 million BahnCards sold, giving Deutsche Bahn AG an overall revenue of $450 million.

4. Theoretical research

Analytical work has focused on the issue of optimality of certain nonlinear pricing schemes under different market conditions such as monopoly and oligopoly. We begin with some broad findings applicable in monopoly settings.

4.1 Monopoly

In a classic paper, Oi (1971) addressed the following question: as an owner of Disneyland, should you charge a high entry (fixed) fee and give the individual rides for free or should you let people come in for free but charge a high price per ride (marginal price)? These two alternatives represent two extremes: either charge a flat fee for entry or a per-ride rate. Oi considered the different roles played by the entry fee and price per ride. He noted that if the monopolist desired to have all consumers in the marketplace be interested in its product, then the entry fee has to be equal to the smallest of consumer surpluses. Next, as the marginal price and entry fee together determine the demand and the overall profit, there is an implicit relationship between the two prices. He showed that a two-part tariff (as opposed to a flat fee or a per-ride rate) will allow a monopolist to be both efficient in allocation and profit maximizing. The allocation efficiency comes from setting the usage price close to the marginal cost and the profit maximization occurs by using the access (or fixed) fee to extract all or most consumer surplus. In addition, the resulting pricing

scheme can be such that a few consumers might be left out of the market (i.e. the entry fee is higher than the minimum of consumer surplus). This reduction in market coverage is compensated by a lower per-ride fee and the subsequent increase in demand for rides from the rest of the market.

In later work, Schmalensee (1981) and Varian (1985) have extended this analysis for situations where the monopolist can price-discriminate and investigated how it changes the welfare implications. Welfare change is the sum of monopoly profits and consumer surplus changes. They found that there is an increase in welfare from a simple monopoly to a price-discriminating monopoly only if the total quantity produced increases. In another extension, Rochet and Stole (2002) showed that even with random participation constraints, the optimal nonlinear pricing scheme takes the form of a two-part tariff.

Recent work has investigated the conditions that can alter the optimal combination of the fixed fee and marginal price in a two-part tariff. Essegaier et al. (2002) consider the dual roles of capacity constraints and usage heterogeneity in the customer base for optimal pricing of access services (e.g. services such as AOL, sports clubs, resorts and cable TV services). They make the following modeling assumptions: there are two consumer segments in the market – heavy users, who account for a fraction α of the market and use d_h units of capacity, and the rest $(1-\alpha)$ are light users who use d_l $(d_l < d_h)$ units of capacity. These usage rates are assumed to be independent of price. Thus the maximum usage rate (assuming the number of customers in the market is normalized to 1) is given by $\bar{d} = \alpha d_h + (1-\alpha)d_l$. This is the maximum capacity that is required to service the entire market. For any given fee (f) and usage price (p), light users pay $P_l = f + pd_l$ and heavy users pay $P_h = f + pd_h$. In addition, they model customer heterogeneity in preference by using the Hotelling line – a consumer who is located at x $(0 \leq x \leq 1)$ has a linear transportation cost of tx to access the monopolist's service, where t is the unit transportation cost. In addition, V is the reservation price for the service (which is assumed to be the same for the two segments).

With these assumptions, they show that in the case of no capacity constraints, a monopolist will charge a flat fee such that it can cover the entire market. This flat fee price is $f = V - t$. The more interesting case arises when there are capacity constraints. The following constrained maximization problem captures the managerial decision:

$$\begin{aligned} &\underset{(f,p)}{\text{Max}}\ (1-\alpha)x_l(f+pd_l) + \alpha x_h(f+pd_h), \\ &\text{subject to } 0 \leq x_l \leq 1,\ 0 \leq x_h \leq 1, \\ &\text{and } (1-\alpha)x_l d_l + \alpha x_h d_h \leq K. \end{aligned} \tag{16.1}$$

Here, K is the capacity of the provider which satisfies, $0 \leq K \leq \bar{d}$ and x_l is $(V - f - pd_l)/t$, which is the location of marginal light users who are just indifferent between buying and not buying. Similarly, x_h is $(V - f - pd_h)/t$, which is the location of heavy users who are just indifferent between buying and not buying. The above maximization problem can be used to calculate what the optimal f and p should be as the capacity K changes. Essegaier et al. perform such an analysis and find that the two pricing components (f, p) should be negatively correlated. The flat fee is an effective way of extracting surplus from light users whereas the heavy users are more sensitive to the usage rate.

Thus, when customers have different usage rates, the pricing policy determines the customer mix that will be present and how much of the constrained capacity will be used. See Oren et al. (1985) and Scotchmer (1985) for other research that relates nonlinear pricing with capacity constraints.

An important question is whether firms should have a fixed fee and other nonlinear pricing plans together in their portfolio of offered plans. Sundararajan (2004) offers some guidelines in this regard. He analyzed a scenario where a firm associated with information goods offered both a fixed fee and a usage-based pricing plan under incomplete information. He found that if there are transaction costs associated with administering the usage-based pricing scheme, then offering a fixed fee pricing scheme (in addition to the usage-based scheme) is always profit improving. In fact, there may be situations (such as an information market in its early stages with a high concentration of low-usage customers) wherein a pure fixed fee pricing is optimal. What about the optimality of other types of nonlinear pricing schedules within a monopolistic setting? In a recent work, Masuda and Whang (2006) show that a portfolio comprising special forms of three-part tariff plans wherein, upon payment of a fixed fee, consumers receive certain units of the service for free and then are charged on a per-unit rate delivers as good a performance as any other nonlinear pricing schedule. Such special forms of three-part tariff are commonly used in the wireless telecommunications industry.

The examples described so far have considered a firm selling only a single product. What happens if the firm sells multiple products? Is a two-part tariff still optimal under some conditions? Armstrong (1999) attacked such a problem with a model that assumed consumers had multiple latent preference parameters, which might or might not be correlated across the products. He finds that if the preference parameters are independently distributed across products, the almost optimal tariff is a two-part tariff. If, however, there is a correlation in the preferences across products, the almost optimal tariff can be implemented as a menu of two-part tariffs. Thus a correlation of consumers' preferences induces a change in the overall optimal pricing scheme. See other work such as Mirman and Sibley (1980) and Wilson (1991) for other examples of optimal multiproduct pricing.

In this section, we have described only a small fraction of the enormous amount of research that has been done in monopoly settings. See Wilson (1993) for a more detailed discussion of such work.

4.2 Oligopoly

For oligopoly settings, researchers have tried to ascertain whether an increase in competition changes the structure of offered nonlinear pricing schemes. The typical modeling framework in such settings has both vertical and horizontal differentiation – the horizontal component captures the preferences of consumers across competitors while the vertical component captures differences in quality (Stole, 1995; Villas-Boas and Schmidt-Bohr, 1999; Armstrong and Vickers, 2001; Ellison, 2005). Stole (1995) showed that as competition increases, the quality distortion (i.e. the classic result that a monopolist will distort the quality level of its offered products to extract higher profits) decreases. Other work (Rochet and Stole, 2002; Armstrong and Vickers, 2001) have also found a similar result. In addition, both Rochet and Stole and Armstrong and Vickers show that, with some simplifying conditions such as full market coverage, the nearly optimal pricing

scheme is again a two-part tariff scheme. One salient aspect of research in oligopoly settings is the rapid increase in mathematical complexity, which constrains researchers from obtaining simple closed-form solutions.

While the two-part tariff scheme can be nearly optimal under many conditions, several firms use more complex pricing schemes. Are such schemes optimal under any circumstance? The recent work of Jensen (2006) provides some direction, albeit in a much simpler duopoly setting. Jensen shows that implementation of simple two-part tariffs may not be a feasible strategy as the optimal nonlinear tariff exhibits a convexity for lower quantities. She shows that an optimal outcome can be implemented if firms use a tariff with inclusive consumption, i.e. a two-tier tariff where consumption on the first tier is free. This is exactly the type of pricing scheme used in wireless services. Such a finding clearly points to some future research that can investigate the implementation of other, more complex, pricing schemes.

5. Empirical research

While theoretical work has addressed the optimality of nonlinear pricing schemes under different conditions, the other two issues – the number of plans and the determination of optimal access fee and marginal prices – are empirically driven (see Section 3). Some researchers have begun to address these latter two questions and we describe such work in this section. To a large extent, however, empirical researchers have been concerned with several critical intermediate steps in modeling demand under nonlinear pricing schemes. Table 16.4 shows a summary of various studies in chronological order. In the table, we also indicate the key issue that a study considered and its main findings. Here we discuss a few of these studies in more detail within the broader framework of key issues.

5.1 Simultaneity of price and consumption

Services typically charge based on some form of a multi-part tariff. Such multi-part pricing induces a two-way dependence of price and consumption – the price influences consumption while the level of consumption depends on the prices charged by a provider. This two-way dependence occurs in many contexts. Examples are utilities such as electricity and water supply (Taylor, 1975; Nordin, 1976; Hausman et al., 1979; Billings and Agthe, 1980; Hewitt and Hanemann, 1995; Reiss and White, 2005), landline telephone services (Park et al., 1983; Train et al., 1987; Kling and Van der Ploeg, 1990; Kridel et al., 1993; Miravete, 2002; Danaher, 2002; Narayanan et al., 2007) and cellular phone (Miravete and Roller, 2004; Miravete, 2007; Iyengar et al., 2007a).

Research on addressing this simultaneity has its roots in labor economics (Hall, 1973; Rosen, 1976; Burtless and Hausman, 1978; Wales and Woodland, 1979; Hausman, 1985; Blomquist, 1996; Moffitt, 1990; Van Soest, 1995; Van Soest et al., 2002). Labor economists are concerned with the prediction of changes in the labor supply when a new tax structure is imposed on people. The early work on labor supply (Hall, 1973) used an ordinary least squares (OLS) approach with hours of work as a dependent variable and the applicable federal income tax rate as an explanatory variable. While OLS is attractive because of its simplicity, it is clearly not a viable option for this application because of the endogeneity of tax rate. When such endogeneity is present, researchers have typically used an instrumental variables (IV) approach (Hausman and Wise, 1976; Hausman et al., 1979). The biggest issue with the IV approach is that in practice it is often difficult to find

Table 16.4 Summary of empirical research on nonlinear pricing

Authors	Objective	Data	Model	Key Findings
Hall (1973)	Establish a relationship between the nonlinearity in tax schedules and number of hours that people work	Survey of Economic Opportunity (SEO) – hourly wage rates, personal characteristics of respondents	Ordinary least squares (OLS)	Effects of demographics, such as age, gender, race on number of work hours
Taylor (1975)	Survey of econometric literature on demand for electricity	Description of several studies	–	Appropriate modeling of demand under nonlinear pricing schemes involves an inclusion of marginal and average prices
Burtless and Hausman (1978)	Demand model with a nonlinear budget set arising from changes in tax rates	Consumer-level work hours, tax rates, wages, non-wage compensation and personal characteristics	Utility-based economic model that allows for maximization under a nonlinear budget	Much lower wage elasticities from tax rate changes than previous reduced-form approaches
Hausman et al. (1979)	Forecast consumer-level electricity usage	Household electricity consumption data	Economic demand model using budget constraints	Electricity usage under both time-of-day and declining block rate are predicted well
Park et al. (1983)	Calculate price elasticity for local telephone calls	Number of calls and minutes of local calls	Heteroskedastic and autocorrelated regression	Very small (about 0.1 or less) price elasticities for both calls and minutes
Dubin and McFadden (1984)	Analysis of residential electricity appliance holdings and consumption	Household-level applicance and electricity consumption data	Discrete/continuous demand model	Estimating demand using OLS without modeling appliance choice leads to an overestimation of the elasticity of demand
Train et al. (1987)	Forecast plan choice and demand for local telephone service	Number and average duration of local calls for a sample of customers	Nested logit	Households respond to a price change by changing their calling patterns more than their calling plans

Table 16.4 (continued)

Authors	Objective	Data	Model	Key Findings
Nunes (2000)	How consumers anticipate product usage during purchase deliberation and how it affects the choice of flat fee versus measured plan	Experimental data/ health club visitation records	NBD model	Consumers employ a break-even model – if expected usage is greater than the break-even, they choose a flat fee plan, otherwise they choose a measured plan
Danaher (2002)	Empirically derive a revenue-maximizing strategy for a two-part tariff with customer defection	Monthly usage and retention data	Regression model which also accounts for attrition	Access and usage prices have different relative effects on demand and attrition
Miravete (2002)	Analyze choice of plan and demand for local telephone service with consumer uncertainty	Monthly usage data on number and duration of calls	Demand model with a distinction between *ex ante* and *ex post* consumer types	There is evidence for *ex ante* and *ex post* asymmetry of information. This has implications for optimal design of plans
Lambrecht and Skiera (2007)	Understand the antecedents of flat fee and pay-per-use bias	Customer transaction data and survey data from an Internet service provider	Binomial logit model	Underestimation of usage is a major reason for pay-per-use bias. In addition, flat fee bias does not significantly increase customer defection
Allenby et al. (2004)	Model consumer choice for packaged goods and account for discrete quantities and quantity discounts	Scanner panel data	Discrete/continuous demand model	Model provides a valid measure of utility to assess changes in consumer welfare with assortment changes

Lambrecht et al. (2007)	Analyze the effect of consumer uncertainty on choice among three-part tariff plans	Customer transaction data from an Internet service provider	Discrete/continuous model	Demand uncertainty decreases consumer surplus and increases provider revenue. Access fee is the main driver of tariff choice
Iyengar et al. (2007a)	Incorporate consumer uncertainty on both quality and usage and model choice among three-part tariffs	Consumer-level monthly usage from a wireless service provider	Discrete/continuous model	Consumer learning can be a win–win for both consumers and provider. There is a 35% increase in customer lifetime value with learning than without
Narayanan et al. (2007)	Incorporate consumers' usage uncertainty and model choice between flat fee and measured plan	Consumer-level monthly usage for local telephone service	Discrete/continuous model	Consumers learn about their usage rapidly when they are on a measured plan and learn very slowly when on a fixed plan
Iyengar et al. (2007b)	Incorporate consumer uncertainty in expected usage and model choice among three-part tariffs	Choice-based conjoint	Utility-based economic model, with an underlying latent usage, in the presence of a nonlinear budget	Utility-based discrete choice model with inferred usage predicts significantly better than a traditional conjoint model

proper instruments and justify their use. Given the deficiency of the IV approach, other methods based on the selectivity bias literature (Heckman, 1979) have been developed (Heckman and MaCurdy, 1981; Reiss and White, 2005).

In a seminal paper, Burtless and Hausman (1978) suggested a technique, which combined theory with econometrics, to address this problem. In a pricing context, an application of this technique involves maximizing a specified utility function subject to the constraints imposed by the pricing scheme. With suitable assumptions on the utility function (quasi-concavity) and under increasing block pricing schemes, such maximization can yield a unique optimal solution. The actual consumption is then modeled as a deviation from this optimal solution. Thus it is not the observed consumption that results from an optimization but rather depends on the optimal consumption, which in turn is influenced by the pricing scheme. Burtless and Hausman termed the deviation between the optimal consumption and actual consumption as the 'optimization error'. A detailed explanation of all past research can be found elsewhere (Hausman, 1985; Moffitt, 1990).

Note that uniqueness of the optimal solution requires the presence of an increasing block pricing scheme. This is because these schemes translate to convex constraints and the maximization of a quasi-concave utility function subject to such constraints has a unique optimum (Hausman, 1985). This uniqueness is not ensured if the pricing scheme is decreasing block (e.g. a quantity discount). In such a case, multiple optima might exist. Thus the utility function will have to be directly evaluated to calculate the overall optimum. See Allenby et al. (2004) for such analysis where they evaluate the effect of quantity discounts on overall demand.

5.2 Endogenous choice and consumption decisions

In many service settings, consumers typically choose from a portfolio of nonlinear pricing tariffs. Thus they not only consume under a nonlinear pricing tariff but also choose that tariff (Dubin and McFadden, 1984; Train et al., 1987; Narayanan et al., 2007). For example, in a wireless service context, consumers choose a calling plan and then decide how many minutes to consume under that chosen plan. Such a process suggests two salient points. One, there is a temporal difference between the two decisions. Two, the choice and consumption decisions are endogenous (Hanemann, 1984; Chiang, 1991; Chintagunta, 1993).

Early research had modeled these two decisions as simultaneous. For instance, Train et al. (1987) used a nested logit model to captures households' choices among local telephone options and the relationship between the choice and the number and average duration of local calls. Here, they assume that choice and usage are simultaneous decisions. Similarly, Dubin and McFadden (1984) model the demand of consumer durables and the use of electricity. Here too, they assume that the two decisions are contemporaneous.

More recent research has focused on how to capture the intertemporal nature of the choice and consumption decisions. For instance, Miravete (2002) investigates how consumers choose between a flat fee and a measured tariff for local telephone service and then consume under the chosen tariff. He models the time lag and any uncertainty in consumers that arises by distinguishing between *ex ante* and *ex post* consumer types. A consumer knows only her *ex ante* type when she makes a choice among the different plans. After

making the choice, she receives a shock, which alters her *ex ante* type to the *ex post* type. It is the *ex post* type that in turn influences the subsequent usage decision. This difference between the *ex ante* type and the *ex post* type captures any change in the information set of consumers due to the sequential nature of the decisions. Specifically, Miravete assumes the following relationship between the *ex ante* and the *ex post* type:

$$\theta = \theta_1\theta_2, \tag{16.2}$$

where θ is the consumer's *ex post* type, θ_1 is the *ex ante* type (known to the consumer at the tariff choice stage) and θ_2 is the shock. Thus the distribution of the *ex post* type is composed of the distribution of the *ex ante* type and the shock.

For model tractability, he makes the following distributional assumptions:

$$\theta_1 \sim Beta\left(1, \frac{1}{\lambda_1}\right). \tag{16.3}$$

and

$$\theta_2 \sim Beta\left(1 + \frac{1}{\lambda_1}, \frac{1}{\lambda} - \frac{1}{\lambda_1}\right). \tag{16.3}$$

With these assumptions, the consumer's *ex post* type has a Beta distribution as well:

$$\theta \sim Beta\left(1, \frac{1}{\lambda}\right). \tag{16.4}$$

With these distributional assumptions, these consumer types are similar to probabilities. The demand function for the telephone service is dependent on the *ex post* type and is specified as follows:

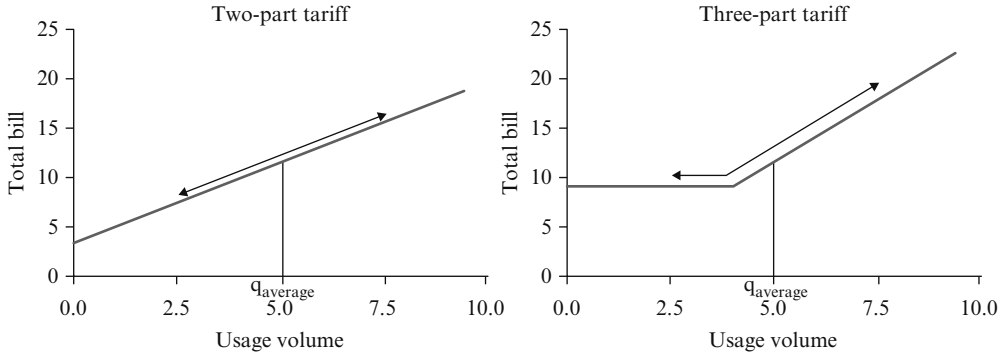
$$x(p, \theta) = \theta_0 + \theta - p, \tag{16.6}$$

where the parameter θ_0 is a parameter large enough to ensure that the demand is always positive and p is the per-minute price. This demand function, together with the distributional assumptions on the *ex post* type, then help Miravete test several hypotheses about how uncertainty plays a role in the sequential decision-making nature of the problem.

A different means for capturing this sequential nature of consumer decisions comes from extending the Burtless and Hausman model to incorporate the choice decision. The intuition is that consumers ascertain the optimal consumption under each available option, evaluate the utility of the different options with that option-specific optimal consumption and then choose the alternative that provides the highest utility. Subsequent to plan choice, consumers' actual consumption deviates from their optimal consumption due to optimization error. Thus the earlier decision of plan choice is influenced by optimal consumption and not the actual consumption. See Section 5.4 for an illustration of this modeling framework.

5.3 Usage uncertainty and learning

The sequential nature of decisions indicates that the information set of consumers could differ from when they are making a choice among different alternatives to when they



Source: Lambrecht et al. (2007), p. 11.

Figure 16.5 Symmetric deviations of usage under a two-part tariff and three-part tariff scheme

are consuming under a chosen plan. Further, if they have the opportunity to engage in repeated choice and usage decisions, their information set might alter over time as they 'learn' and resolve the uncertainty about their own usage patterns.

Lambrecht et al. (2007) use a simple example to show how such usage uncertainty can affect consumer choice. They consider symmetric distributions of usage under a two-part tariff and a three-part tariff. Figure 16.5 shows these deviations. The figure shows that usage deviations under a two-part tariff leave the expected bill unaffected, i.e. the expected bill is the same with low or high levels of uncertainty in usage. This is not so under a three-part tariff – under such pricing schemes, the higher the uncertainty in usage given the same level of mean usage, the higher is the overall bill. This clearly suggests that, under a three-part tariff and more complex multi-part tariffs, consumers' usage expectation can influence their choice of service plan.

Several researchers have found evidence to support this hypothesis (Nunes, 2000; Lemon et al., 2002; Lambrecht and Skiera, 2006). For instance, Nunes (2000) explores the cognitive process of how people anticipate service usage and how they integrate their expectations of usage to choose between a flat fee plan and a measured (pay-per-use) plan. He proposes that consumers calculate a break-even number and then see whether the break-even implies a choice of flat fee plan or a measured plan. Similarly, Lemon et al. (2002) show that consumer expectations of future usage influence their decision to stay with or leave a service provider.

Other researchers have quantitatively investigated consumers' usage uncertainty and learning using sophisticated models that incorporate Bayesian updating. For instance, Goettler and Clay (2007) capture consumer uncertainty and learning about the quality of an online retailer. Similarly, Narayanan et al. (2007) analyze data from an experiment conducted by South Central Bell. In this experiment, people had a choice between a flat rate pricing scheme and a two-part tariff. They find that consumer learning is very rapid when consumers are on the two-part tariff scheme but is very low while on the flat fee plan. Specifically, they make the following modeling assumption for the conditional indirect utility function for consumer i, plan j and time t:

$$V_{it}^{j} = (y_i - f^j) + \frac{\theta_{it}}{\beta}\exp(-\beta p_t^j). \tag{16.7}$$

Here, y_i is the income, θ_{it} is the consumer-specific and time-specific type (similar in spirit to the consumer type proposed by Miravete (2002)), f^j and p_t^j are the access fees and per-unit usage price and the parameter $-\beta$ is the price coefficient.

In addition, Narayanan et al. decompose the type parameter (θ_{it}) in the following manner:

$$\ln(\theta_{it}) = \alpha_i + \gamma Z_{it} + \eta_{it} + \nu_{it} \tag{16.8}$$

Here, the first component α_i is consumer specific but time invariant, the term $(\gamma Z_{it} + \eta_{it})$ captures the component observed by the consumer at the time of plan choice and finally, the shock ν_{it} is unobservable to the consumer during plan choice but is known at the time of usage decision. This framework captures the sequential nature of choice and consumption decisions. To capture learning, Narayanan et al. assume that consumers have beliefs over the parameter α_i, and these beliefs get updated as they observe their choices and the consumption signal.

Note that the above model is developed for a choice between a flat fee and a two-part tariff scheme. It is not straightforward to extend it to a setting where the pricing scheme has multiple tiers. Recently, Iyengar et al. (2007) developed a model that captured consumer learning and uncertainty within the context of more general pricing schemes. They found that consumer learning can lead to a win–win situation for both consumers and the firm – consumers leave fewer minutes on the table while the firm sees an increase in overall customer lifetime value (CLV). In particular, they estimated that there is about a 35 percent increase in CLV (about $75) in the presence of consumer learning. The key driver of this difference is the change in the retention rate with and without consumer learning.

Such quantitative models shed light on how different aspects of the pricing scheme and past choice and consumption decisions can affect consumers' information set and thereby influence their future decisions. While such work provides a direction, there are still many unresolved issues. For instance, within service settings, all models of consumer learning assume that each month's usage gives a signal to the consumer to better understand their own consumption pattern. However, there is research in a scanner data context that suggests that consumers have thresholds of insensitivity (Han et al., 2001). It is certainly plausible to assume that this might be the case within service contexts as well, i.e. perhaps only usage signals that are either above or below some threshold (which could be a function of how many free minutes are associated with the plan) have the potential to affect consumer learning. Such questions have much managerial significance given that consumer uncertainty and learning can affect their decision to defect from a service provider and thereby impact their overall lifetime value.

Thus far, we have given examples of how different researchers have addressed each of the issues associated with modeling consumer decisions under nonlinear pricing schemes. Next, we illustrate an integrated modeling framework that captures all three issues. See Iyengar et al. (2007) for more details. For this example, we use the context of wireless services.

5.4 Integrated modeling framework – example from wireless services

Consider a wireless service that has a two-tier increasing block pricing structure characterized by a fixed fee and two marginal prices. This scheme was graphically shown in Figure 16.1. Suppose F represents the access price for the service and the applicable marginal price is p_1 for consuming an additional unit before the kink is less than the marginal price, p_2, for consuming after the kink.

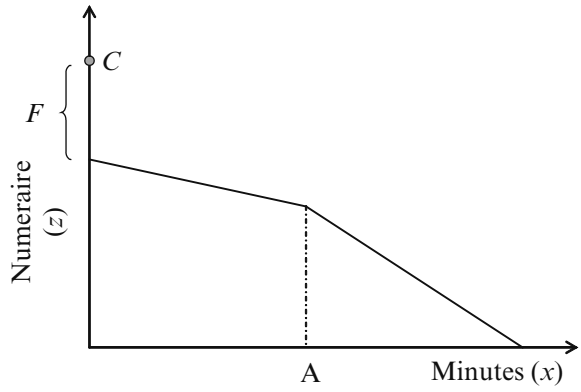
When consumers choose a wireless service, they do not make this decision in isolation from their other consumption decisions. At any point in time, they have several consumption opportunities and they allocate their income among these opportunities. This tradeoff across goods can be appropriately represented using a budget set representation. Such a budget set corresponding to an increasing two-tier pricing scheme is shown in Figure 16.6. The vertical axis in the figure corresponds to the consumption of the outside good (z) and the horizontal axis corresponds to the consumption of units of the service (x).

Figure 16.6 shows that the two-tier increasing block pricing structure of the service results in a piecewise linear budget set with a kink point (A). A consumer who subscribes to the service faces a convex budget set, and her income (I) is lowered by the sum of the access fee (F) and the variable charges for any consumed service. If, however, she does not subscribe to the service, then the entire income is used for consuming the outside good. If the marginal price of the outside good is normalized to 1 (numeraire), then the following equations represent the piecewise budget set.

$$p_1 x + z \leq I - F \quad \text{if} \quad x > 0 \quad \text{and} \quad x \leq A \tag{16.9}$$

$$p_2(x - A) + z \leq I - F - p_1 A \quad \text{if} \quad x > A \tag{16.10}$$

In the wireless communications industry, a restricted form of such a two-tier increasing block pricing scheme, where p_1 is 0, is widely used. Therefore the consumption of an addi-



Note: F refers to the access fee, A is the kink point (free minutes) and C is the total income used for consuming the outside good if the consumer does not subscribe to the plan.

Figure 16.6 A budget set representation of a two-tier increasing block pricing scheme

tional minute before the kink point is costless. Next, we specify the utility that a consumer receives when he/she uses the wireless service.

Utility function Let U_{ijt} be the direct utility function for a consumer i for consuming x_{ijt} minutes under a plan j and a quantity z_{ijt} of the numeraire commodity during period t. We specify U_{ijt} as

$$U_{ijt}(x_{ijt}, z_{ijt}) = \hat{a}_{ij} + \acute{a}_{i1}x_{ijt} + \acute{a}_{i2}z_{ijt} + \acute{a}_{i3}x_{ijt}^2 + \mathring{a}_{ijt}. \tag{16.11}$$

The terms $\hat{a}_{ij}$, $\acute{a}_{i1}$, $\acute{a}_{i2}$ and $\acute{a}_{i3}$ are individual-level parameters[1] and the random choice errors are contained in $\mathring{a}_{ijt}$. We assume that this choice error is double exponential.

The optimal consumption, x^*, which maximizes the direct utility in Equation (16.11) subject to the non-linear pricing constraints imposed by plan j, can be written as follows:

$$\begin{aligned}
&\operatorname*{Max}_{x}\ U_{ijt}(x, z(x)) \\
&\text{subject to Constraint I: } p_{1j}x + z = I_i - F_j, \quad \text{if } 0 < x \leq A_j, \\
&\text{Constraint II: } p_{2j}(x - A_j) + z = I_i - F_j - p_{1j}A_j, \quad \text{if } A_j < x < B.
\end{aligned} \tag{16.12}$$

To ensure a unique solution to the above maximization problem, the utility function should be quasi-concave. This requires the Slutsky constraints $-\acute{a}_{i2} > 0$ and $\acute{a}_{i3} < 0$ on the parameters of the utility function. For a quasi-concave utility function and a convex budget set, the unique optimal solution x^* can be at an interior point (between 0 and A_j or between A_j and B) or one of the end points – 0, A_j and B. The two candidates for an interior optimal solution can be found by maximizing the utility function subject to the two linear constraints. The first-order conditions yield the following two interior candidate optima:

$$x^{candopt,I} = \frac{\acute{a}_{i2}p_{1j} - \acute{a}_{i1}}{2\acute{a}_{i3}},$$

$$x^{candopt,II} = \frac{\acute{a}_{i2}p_{2j} - \acute{a}_{i1}}{2\acute{a}_{i3}}, \tag{16.13}$$

In the above equations, $x^{candopt,I}$ ($x^{candopt,II}$) refers to the candidate optimal consumption when the utility function is maximized with Constraint I (Constraint II).

Given the uniqueness of the solution, at most one of the two candidates will be attainable, i.e. will lie in the consumption interval where its applied constraint holds. As Constraint I holds for any positive consumption less than A_j minutes, even though $x^{candopt,I}$ can lie anywhere on the real line, it is attainable only if it lies between 0 and A_j minutes. Similarly, $x^{candopt,II}$ is attainable only if it lies between A_j minutes and B. It is, however, possible that none of two candidates for an interior solution is attainable. Then, one of end points (0, A_j or B) might be chosen. These cases are mutually exclusive and, together with any possible

[1] The term $\hat{a}_{ij}$ represents an individual and plan-specific intercept. The parameter $\acute{a}_{i1}$ represents the main effect of consumption of minutes and $\acute{a}_{i2}$ represents the effect of consuming a unit of the numeraire. The term $\acute{a}_{i3}$ captures the effect of differential marginal impact of consuming an additional minute.

interior solution, form an exhaustive solution set, i.e. $x^* \in \{0, A_j, B, x^{candopt,I}, x^{candopt,II}\}$. We denote this optimal quantity for consumer i, plan j and time t by x^*_{ijt}.

Let the actual demand under plan j for consumer i at time t be x^{act}_{ijt}, then the optimal demand is related to the actual demand in the following manner:

$$x^{act}_{ijt} = x^*_{ijt} + \eta_{ijt}. \tag{16.14}$$

Here, the demand error, η_{ijt}, is assumed to be normally distributed with a mean 0 and variance δ^2. Thus the actual demand is a function of the optimal demand, which in turn is dependent on the budget constraints imposed by the pricing scheme. Equation (16.14) can then be used to determine the likelihood of consuming a certain number of minutes under a given plan.

Note that we developed this model for a scenario where consumers were facing an increasing block pricing scheme. As discussed earlier, such a scheme results in a convex budget set, and together with a quasi-concave utility function, we obtain a unique optimal quantity. This uniqueness is not ensured if the pricing scheme is decreasing block (e.g. a quantity discount). In such a case, multiple optima might exist and the algorithm for finding the optima (see equation 16.12 and the following discussion) will not be applicable. Thus the utility function will have to be directly evaluated to calculate the overall optimum. See Allenby et al. (2004) for such analysis where they evaluate the effect of quantity discounts on overall demand.

In addition, the above example shows that the Burtless and Hausman model primarily investigated demand under a nonlinear budget set. In several service contexts, however, such a model captures only one part of consumers' decisions. For example, in the wireless service context, consumers choose a calling plan among several alternatives and then consume under the chosen plan. Next, we describe how the above model can be extended to include the choice decision.

5.4.1 Inclusion of choice decision To incorporate the choice decision within the above framework, we calculate the optimal consumption associated with every plan. Thus, for every service plan k ($k = 1 \ldots J$), let the optimal consumption be x^*_{ikt}. Next, we determine the utility corresponding to this optimal consumption. This is the maximum utility that consumer i will receive if he or she chooses alternative k. Let the systematic component be denoted by V_{ikt}. Thus

$$U^{\max}_{ikt}(x^*_{ikt}) = V_{ikt} + \mathring{a}_{ikt}. \tag{16.15}$$

Recall that we assumed that the choice error is double exponential distributed. This assumption gives the familiar logit expression for the probability of choice:

$$P_{ijt} = \frac{e^{V_{ijt}}}{\sum_k e^{V_{ikt}}} \tag{16.16}$$

Equations (16.14) and (16.16) together give the likelihood of choosing plan j and consuming x^{act}_{ijt} minutes. In this model, the choice and consumption decisions are related via the optimal quantity, which in turn is determined by maximizing the utility function

subject to the budget constraints. Thus both consumer decisions stem from a single utility function. In addition, the choice decision occurs before the consumption decision and is influenced by optimal consumption.

Note that so far in this framework, we have assumed that consumers are completely certain of their optimal consumption under the different plans. Next, we show a way in which such uncertainty can be incorporated within the model.

5.4.2 Consumption uncertainty If consumers have uncertainty in their consumption, then it renders the utility function stochastic. In such situations, consumers will use expected utility for making any decisions. This can be represented as follows:

$$\begin{aligned} EU_{ijt} &= E^{t}_{usage}[g(x_{ijt}, z_{ijt})] + \hat{a}_{ij} + \mathring{a}_{ijt}, \\ g(x_{ijt}, z_{ijt}) &= \acute{a}_{i1}x_{ijt} + \acute{a}_{i2}z_{ijt} + \acute{a}_{i3}x^{2}_{ijt}. \end{aligned} \tag{16.17}$$

Here, EU_{ijt} refers to the expected utility for consumer i and plan j and the term $E^{t}_{usage}[g(x_{ijt}, z_{ijt})]$ is the expectation with respect to a consumer's beliefs about his/her own usage. For each plan j we can assume an individual-specific belief distribution denoted by $f^{usage}_{ijt}(x)$. We subscript this belief distribution by time 't' to denote that it might be changing over time due to consumer learning. Different assumptions made for this belief distribution can investigate its sensitivity on the findings.

Thus, using the quantity belief distribution and the plan-specific budget constraints, the component, $E^{t}_{usage}[.]$, can be computed. The budget constraints for the plan impose a relationship between the consumed minutes (x_{ijt}) and the numeraire (z_{ijt}) as shown in equations (16.9 and 16.10). For example, if Constraint I holds, then $z_{ijt} = I_i - F_j - p_{1j}x_{ijt}$. Similarly, if Constraint II holds, then $z_{ijt} = I_i - F_j - p_{1j}A_j - p_{2j}(x_{ijt} - A_j)$. In other words, we can rewrite $g(x_{ijt}, z_{ijt})$ as a function of x_{ijt} only. Let $g(x_{ijt}, z_{ijt})$ be denoted by $h_1(x_{ijt})$ if $x_{ijt} \leq A_j$ and by $h_2(x_{ijt})$ if $x_{ijt} > A_j$. The quantity expectation is as follows:

$$E^{t}_{usage}[g(x_{ijt}, z_{ijt})] = \int_{0}^{A_j} h_1(x) f^{usage}_{ijt}(x)\,dx + \int_{Aj}^{\infty} h_2(x) f^{usage}_{ijt}(x)\,dx. \tag{16.18}$$

This expected quantity can be re-inserted in equation (16.17) to give the overall utility function. As before, if we continue to assume that the choice errors are double exponential distributed, then we can write the probability of choice for a plan with the familiar logit expression. This probability expression now would incorporate the effect of consumption uncertainty on plan choice. This completes our integrated modeling framework.

5.5 Key empirical results

Several empirical studies have focused on how consumers behave under nonlinear pricing schemes and then capture how the different components of a multi-part pricing scheme affect their behavior. Here, we summarize some key empirical results.

5.5.1 Flat fee bias A robust finding across many empirical studies is that many consumers prefer a tariff with a flat fee even though their overall expense will be lower on

a pay-per-use plan (Kling and Van der Ploeg, 1990; Kridel et al., 1993; Nunes, 2000; Lambrecht and Skiera, 2006). This is referred to as the 'flat fee' bias. For instance, within the context of long-distance telephone service, Kridel et al. (1993) had found that 65 percent of consumers showed a flat fee bias. Similarly, in an application involving the use of an Internet service, Lambrecht and Skiera (2006) find that about 48 percent of consumers show a flat rate bias.

Lambrecht and Skiera (2006) also systematically consider the various causes for this bias and suggest that there are four reasons for its existence: insurance effect, taxi meter effect, convenience effect and overestimation effect. Insurance effect refers to the notion that consumers might want to choose a flat fee option as they want to 'insure' against future variation in their usage. The taxi meter effect captures the fact that many consumers can find their use of the service less enjoyable if they are paying by the minute. The term 'convenience effect' points to consumers choosing a status quo tariff to minimize any mental hassle associated with calculating the expected cost under the different available alternatives. Finally, the overestimation effect refers to the empirical finding that consumers can overestimate their demand, thereby biasing their choice towards a plan with a flat fee. In their study, Lambrecht and Skiera find that the insurance, taxi meter and overestimation effects account for the flat fee bias. Clearly, the level of consumers' usage uncertainty can moderate which of the four factors will have an influence on his/her choice decision.

5.5.2 Differential effect of access fee/marginal price A second empirical generalization is that the different components of a pricing scheme indeed have a differential impact on customer behavior. We discuss two aspects: price elasticity and the use of the multi-part tariff for discrimination.

1. *Price elasticity* Several studies across different contexts have investigated the price elasticity of different components of a multi-part pricing scheme. They have typically found price elasticity ranging from 0.1 to 1.0. Danaher (2002) describes a market experiment for a new telecommunication product (like a wireless service) in which the pricing scheme (a two-part tariff) was systematically manipulated. Consumers had to make a decision whether to continue using the product and if so, how much to use it. In that context, he found that both access fee and marginal price elasticity to be lower than 1.0. Within wireless services, Reiss and White (2007) also find that the mean price elasticity is less than one (1.00) and estimate it to be −0.44. Two studies in the context of local telephone service find very similar numbers – Park et al. (1983) and Train et al. (1987) found the price elasticity to be between 0.1 and 1.0. See Manfrim and Da Silva (2007) for a summary of estimated price elasticity across several different studies.
2. *Price discrimination* Iyengar (2007) reports that changes in access fee have a much larger impact on customer lifetime value (CLV) as compared to that from changes in marginal price. He analyzed consumers' choice among four wireless service plans and their decision to leave the service provider. Each of these plans had a three-part tariff structure – access fee, associated free minutes and a per-minute rate for any consumed minutes beyond the free minutes. Table 16.5 shows the details of the pricing scheme for the four plans. After estimating the model parameters, he then

Table 16.5 Elasticity of customer lifetime value with increase or decrease in prices

Plan	Access fee ($)	Free minutes	Per-minute rate ($/min)	Access fee		Per-minute rate	
				up	down	up	down
1	30	200	0.40	−1.18	1.08	–0.02	0.09
2	35	300	0.40	−0.09	0.09	–0.06	0.08
3	40	350	0.40	−0.48	0.25	–0.12	0.10
4	50	500	0.40	0.06	−0.09	–0.22	0.16

Source: Iyengar (2007).

performed simulation studies to capture consumers' choice and consumption decisions (which provide revenue to the service provider) and their decision to stay with or leave the provider (consumers' defection decision). He then combined the generated revenue and consumers' defection decision to determine their CLV. In addition, he calculated the elasticity of CLV with respect to both access fee and marginal price. In these simulations, he changed (either increased or decreased) the access fee and marginal prices of the four plans, one plan at a time. Table 16.5 shows the results of the simulations.

The table shows that, in general, a price decrease for a plan leads to a higher CLV than that from an equivalent price increase. A price increase for a plan results in higher average revenue per user (ARPU) but negatively affects retention. In contrast, a price decrease for a plan enhances retention but lowers the revenue. The CLV results suggest that an increase in retention is more effective for increasing the CLV than an increase in the revenue. He also finds that for all plans but Plan 4, the elasticity of CLV with respect to the access price for a plan is higher than with respect to its marginal price. Thus service providers can affect the CLV more by changing the access fee than by altering the marginal prices.

An analysis of the effects of changing the access price on the CLV shows that a decrease in the access price for Plan 1 has the highest effect. This effect on CLV can be decomposed into the effect on revenue and retention. Table 16.6 shows this decomposition.

The table shows that the primary contributor for this result is an increase in retention of the 'light users' on Plan 1. Interestingly, he finds that an increase in the access price for Plan 4 leads to a higher CLV than that arising from a price decrease. This result can be explained based on the tradeoff between the ARPU and retention. The table shows that for a change in the access price of Plan 4, the ARPU is more elastic than retention is. Hence the increase in the ARPU due to an increase in the access fee dominates the decrease in retention and thereby yields a higher CLV than that of the base case scenario. An analysis of the effects of changing the marginal price on the CLV reveals that an increase in the marginal price for Plan 4 has the highest effect. This result is due to the increase in the defection rate of 'heavy users' on Plan 4. These consumers have a high consumption of minutes and can only respond to a price increase by defecting since downgrading to lower plans is not attractive. In contrast, a decrease in the marginal price for Plan 4 generates an incentive for

Table 16.6 Elasticity of ARPU and retention with increase or decrease in prices

Plan	Elasticity of ARPU				Elasticity of retention			
	Access fee		Per-minute rate		Access fee		Per-minute rate	
	up	down	up	down	up	down	up	down
1	0.23	−0.24	0.16	−0.07	−0.68	0.58	−0.08	0.07
2	0.11	−0.12	0.02	−0.01	−0.10	0.10	−0.03	0.04
3	0.24	−0.27	0.01	−0.01	−0.34	0.24	−0.05	0.04
4	0.10	−0.09	0.01	−0.02	−0.03	0.01	−0.11	0.08

Source: Iyengar (2007).

these heavy users to stay longer with the company. These findings suggest that the different components of a multi-part pricing scheme can be effectively used for price discrimination.

Iyengar et al. (2007b) provide additional evidence in support of the differing effect of access fee and marginal prices on consumers' choice decisions. With data from a choice-based conjoint task using multi-part tariffs, they build an economics-based model to investigate how changes in the pricing scheme of plans affect its probability of choice. They find that changes in access fee affect the plan choice probability in a way that differs both qualitatively and quantitatively from those by changes in the marginal prices. Specifically, they find that above a certain threshold, an increase in marginal price of plan does not have any effect on the consumer choice decision. In contrast, any increase in access fee of a plan always reduces the probability of choice of that plan.

Iyengar et al. also address questions regarding optimal (profit-maximizing) values of access fee and marginal price for the available plans. They use individual-level parameter estimates, e.g. price sensitivity, to account for customer heterogeneity and calculate the value of access fee and marginal prices for a portfolio of plans, which would lead to maximum overall profit. Such an analysis combines economic theory with customer behavior under such a pricing structure to yield profit-maximizing values for the various components of the pricing scheme.

In summary, these findings suggest that components of a pricing scheme can have a systematically differential impact on customer behavior. It is only recently that researchers have started investigating such effects, which suggests that this area holds much promise for future investigations.

6. Conclusions

In this chapter, we discussed several aspects of nonlinear (or multi-part) pricing. Such pricing schemes are very common in the service industry. We began the chapter by discussing several reasons for the use of such schemes and noted that the primary factor is the heterogeneity of the customer base. Such heterogeneity of preferences leads customers to choose different pricing plans based on their expected demand.

Next, we discussed findings from analytical work on nonlinear pricing. Here, we

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