6 Structural models of pricing

*Tat Chan, Vrinda Kadiyali and Ping Xiao**

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

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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 $(\gamma^k_{ij}, \beta^k_i, \alpha^k_i)$ 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:

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

The manufacturer m's objective function is the following:

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

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^k_j 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^V_{it}, 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:

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

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

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

where $\gamma_{j'j}$ 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:

$$S_{jt}^k = \frac{\exp(\gamma_{ij} + x_{jt}\beta_i - \alpha_i p_{jt} + \xi_{jt})}{1 + \sum_{j'=1}^{J} \exp(x_{j't}\beta^k - \alpha^k p_{j't} + \xi_{j't})} \tag{6.10}$$

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

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

[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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