Marketing Letters 16:3/4, 209–224, 2005

Recent Advances in Structural Econometric Modeling: Dynamics, Product Positioning and Entry

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Abstract

In the empirical analysis of consumer markets, recent literature has begun to explore the dynamics in both consumer decisions as well as in firms' marketing policies. Other research has begun to explore the strategic aspects of product line design in a competitive environment. In both cases, structural models have given us new insights into consumer and firm behavior. For example, incorporating consumer and firm dynamics may help explain patterns in our data that are not well-captured by static models. Similarly, the strategic aspects of firm entry and

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product-positioning may be intrinsically linked to firm conduct and the intensity of competition in a market. Structural analysis of these consumer and firm decisions raise a number of substantial computational challenges. We discuss the computational challenges as well as specific empirical applications. The discussions are based on the session "Structural Models of Strategic Choice" from the 2004 Choice Symposium.

Keywords: entry, dynamics, market structure, product positioning, structural models

1. Introduction

In recent years, there has been a growing focus in marketing and economics on the estimation of structural models of consumer and firm behavior. A structural approach generates estimates of an underlying behavioral trait of the agent (firm or consumer). These estimates are considered invariant to changes in the environment in which the data are generated and, consequently, are not subject to the "Lucas Critique" (Lucas, 1976). Hence, the estimates can be used to perform policy analysis. For example, one might investigate how market outcomes change when firm decisions (e.g., marketing mix decisions, entry/exit decisions) are changed. In contrast, model estimates from descriptive regressions may vary as firm decisions change, and hence the estimates cannot be used for optimizing firm decisions. We refer the interested reader to the comprehensive survey by Reiss and Wolak (2004) for a thorough discussion of structural versus descriptive econometric models.

Until recently, most structural work in markets for consumer goods has focused on demand system estimation and pricing (see the survey in Dubé et al. (2001) for examples). Recently, we have seen two major developments. First, a growing body of research incorporates consumer and firm dynamics. A second literature has begun to model strategic marketing decisions for variables other than prices. Most notably, the strategic aspects of product launch and product positioning are slowly emerging as an important topic in the structural literature. While these topics have long been a staple of theoretical analysis, they are rarely treated seriously in structural estimation due to a number of modeling and computational challenges. The survey discusses these issues.

Incorporating consumer and firm dynamics into structural econometric models enhances our understanding of behavior. A structural approach takes into account the fact that when current choices influence future pay-offs, then the behavior of a rational decision-maker must be forward-looking. Such dynamic models may be able to explain certain empirical patterns that are not captured by a static model. Furthermore, as we begin to consider more sophisticated models of consumer dynamics, we may also need to develop methods to address the resulting dynamics on the supply-side. Researchers frequently specify game-theoretic supply-side models to avoid potential endogeneity bias in the estimation of demand parameters. If firms account for the future implications of their actions on consumer behavior, then a dynamic supply-side model may need to be employed accordingly. We discuss empirical examples that generalize across many consumer goods markets.

In principle, estimating structural parameters that are consistent with a dynamic model may require solving a dynamic programming problem at each iteration of the estimation procedure. A potential computational concern arises depending on the dimensionality of the problem. We discuss several methods for estimating parameters that are consistent with the optimality conditions of the dynamic program, but that do not require solving it at each iteration of the estimation procedure.

Structural models of entry and product positioning are a fairly recent addition to the literature. The relative ease with which a firm may adjust its prices, advertising and promotional decisions has facilitated the collection of data with substantial variation in these variables. As a consequence, researchers have tended to focus their attention on short-run marketing instruments. Longer-run decisions, such as a firm's decision to enter a market and subsequent product positioning have been routinely maintained as exogenous, primarily for technical convenience because in most datasets there is not much variation in these variables. The empirical analysis of product entry and "type" choice is of interest to researchers for two reasons. Substantively, the analysis of product entry and product positioning can teach us about the formation of long-run market structures. Econometrically, the endogeneity of product "type" choice also raises a potential source of endogeneity bias in the estimation of demand systems, in addition to the established endogeneity of prices (e.g. Berry, 1994; Villas-Boas and Winer, 1999).

The remainder of this paper is organized as follows. The second section discusses the substantive and computational issues involved with dynamics. The emphasis is on a narrow class of dynamic behavior whereby agents use Markov (or pay-off-relevant "state-dependent") decision rules. In the third section, we discuss firm entry and product positioning. We conclude in the fourth section.

2. Dynamics

There are two important reasons for incorporating dynamics into structural empirical models for consumer goods markets. Substantively, the dynamics may be more "realistic" and, hence, may provide a better description of behavior. More importantly, there may be patterns in the data that are simply not captured by a static model. Hence, ignoring the dynamics could potentially "throw away" valuable information and, worse, could generate misleading conclusions about behavior.

Typical consumer data in repeat purchase environments (e.g. grocery) routinely exhibit patterns suggestive of choice dynamics. For example, researchers have documented that the observed time-between shopping trips is longer for consumers whose previous purchase occurred during a sale week (Blattberg and Neslin, 1990, Hendel and Nevo, 2003). This result, the "post-promotion dip" (Blattberg and Neslin, 1990), is consistent with stock-piling behavior. A similar "pre-promotion dip" has been documented (Van Heerde et al., 2001), consistent with consumers delaying purchases in anticipation of predictable sales.

Only recently have researchers been able to estimate structural models that capture the dynamics associated with stock-piling with (rational) price expectations (Gonul and Srinivasan, 1996; Erdem et al., 2003; Hendel and Nevo, 2003). In a related context, Hartmann (2004) studies the consumption of a leisure activity, golf. While rounds of golf are not inherently storable, the experience may generate a lasting stock of satisfaction that can explain the observed time intervals between an individual's rounds played and the impact of occasional discount coupons. Measuring the rate at which this satisfaction depreciates over time can be helpful for fine-tuning occasional price promotions or setting prices more generally for these types of goods. Related work has also accommodated changing demand over time due to consumer learning in the presence of advertising (Erdem and Keane, 1996; Ackerberg, 2003; Crawford and Shum, 2003).

Dynamics can also arise on the supply side when firms's marketing decisions require them to be forward-looking. For example, the carry-over effects of current marketing decisions such as advertising and price promotions may have lasting effects over time (see survey by Clarke (1976)). Marketing data often reveal that prices and advertising can exhibit systematic patterns over time that may not be well-explained by static models. For example, prices are subject to occasional temporary price cuts. In the grocery context, these patterns have been explained empirically as inter-temporal price discrimination (Pesendorfer, 2003; Aguirregabiria, 2002) and as sticky prices due to adjustment costs (Slade, 1998). Advertising exhibits a similar temporal pattern, with long spells of weeks with no advertising followed by short-bursts of advertising weeks. Empirically, this practice, referred to as "pulsing," has been explained by non-convexities in the impact of advertising on demand such as an S-shaped response function (Villas-Boas, 1993) or a threshold in consumer response to advertising (Dubé et al., 2004).

In each of these examples, current decisions by agents (e.g. firms and/or consumers) influence future pay-offs. Hence, rational agents should make forward-looking decisions. There are a number of technical challenges in the derivation and estimation of structural empirical models that are consistent with such forward-looking decision-making. We discuss these next.

2.1. A Framework for Dynamic Programming Problems

We focus our discussion on dynamic programming problems with Markov, or pay-off-relevant "state-dependent", choices. Agents are assumed to make decisions based only on historic information directly related to current pay-offs. That is, history only influences current decisions insofar as it impacts a state variable that summarizes the direct influence of the past on current pay-offs. For competitive environments, we use the Markov Perfect Equilibrium concept, a profile of Markov strategies that yields a Nash equilibrium in every proper subgame. In both theoretical and empirical research, the restriction to Markov strategies simplifies the analysis of dynamics in complex environments. "Markov strategies prescribe the simplest form of behavior that is consistent with rationality" (Maskin and Tirole, 2001). From an empirical perspective, Markov strategies depend on as few variables as possible, reducing the number of parameters to be estimated. More general closed-loop equilibrium concepts that look at the entire history of the game (i.e. not just the pay-off relevant history) have been used in empirical models for games with simpler forms that can be solved analytically (see Erickson, 1995 for a survey). Similarly, the literature on collusion in repeated games frequently considers non-Markov strategies that depend on past play (Green and Porter, 1984; Porter, 1983). In the following discussion, we focus on Markov games that cannot be solved analytically.

We begin with a discussion of a single-agent model. For example, the agent could be a consumer whose current product choice could influence her preferences during future shopping trips. Consider the set of possible states $g \in \Gamma$. For a realization of the state g, the agent takes the action $\sigma(g) \in \Omega$. We assume the vector g has a Markov transition density $p(g_{t+1}|g_t, \sigma_t)$. The dependence of $p(g_{t+1}|g_t, \sigma_t)$ on actions σ_t reflects the fact that current decisions may influence future pay-offs (i.e. a "controllable" state). Since current actions influence future realizations of the state, a rational agent should make forward-looking decisions. The expected present discounted value (PDV) of pay-offs under the current state g_t and the decision-rule σ is:

$$V(g_t \mid \sigma) = \mathbb{E}\left[\sum_{s=t}^{\infty} \beta^{s-t} \pi(g_s, \sigma(g_s)) \mid g_t\right] \tag{1}$$

where β is a discount factor and $\pi(g, \sigma)$ is the current pay-off of action $\sigma(g)$ and state g. Expectations are taken over an additional random disturbance to current returns. Depending on the context, the pay-off function (1) could be the discounted sum of future utility, for a dynamic consumer choice problem, or the discounted sum of profits, for a forward-looking firm. Optimal decisions are described by a value function that satisfies the *Bellman equation*:

$$V(g \mid \sigma) = \sup_{\sigma} \left\{ \pi(g, \sigma) + \beta \int V(g' \mid \sigma) p(g' \mid g, \sigma(g))\, dg' \right\}. \tag{2}$$

Under certain conditions, the Bellman equation forms a contraction-mapping. Hence, this recursive formulation can provide a convenient basis for solving the agent's dynamic programming problem (DP).

Introducing competition is relatively straightforward. The multi-agent analog of the model merely requires some additional notation. First, a strategy profile $\sigma = (\sigma_1, \ldots, \sigma_J)$ lists the decision rules of all J agents. The expected present discounted value (PDV) of pay-offs for agent j under the current state g_t and the strategy profile σ is

$$V_j(g_t \mid \sigma) = \mathbb{E}\left[\sum_{s=t}^{\infty} \beta^{s-t} \pi_j(g_s, \sigma(g_s)) \mid g_t\right] \tag{3}$$

As in the single-agent case, optimal decisions are described by a value function, one for each agent, that satisfies the *Bellman equation*:

$$V_j(g \mid \sigma) = \sup_{\sigma_j} \left\{ \pi_j(g, \sigma_j, \sigma_{-j}(g)) + \beta \int V_j(g' \mid \sigma) p(g' \mid g, \sigma(g)) dg' \right\}. \tag{4}$$

This Bellman equation is defined with respect to a specific competitive strategy profile σ_{-j}, i.e. a specific guess about the behavior of the firm's competitors. The right-hand side of the Bellman equation defines the best response to σ_{-j}. A Markov perfect equilibrium (MPE) of the dynamic game is a list of strategies, $\sigma^* = (\sigma_1^*, \ldots, \sigma_J^*)$, such that each σ_j^* is a best response to σ_{-j}^*. More formally, the strategy profile σ^* satisfies $V_j(g \mid \sigma^*) \geq \pi_j(g, \sigma, \sigma_{-j}^*(g)) + \beta \int V_j(g' \mid \sigma^*) p(g'|g, \sigma, \sigma_{-j}^*(g))$ for all unilateral deviations σ, states

g, and firms j.[1] Unlike the single-agent case, the Bellman equation may no-longer be a contraction-mapping in multi-agent environments.

A MPE in pure strategies for the types of dynamic games described above need not exist, and if it exists, it need not be unique. In some instances, existence of equilibria can be determined ex ante, and evaluated numerically (e.g. Ericson and Pakes, 1995). In other cases, especially in empirical contexts, it may be sufficient to determine whether an equilibrium exists at estimated parameter values. Existence for a specific case can be checked automatically by a numerical solution algorithm. Although it would not guarantee uniqueness, if this algorithm converges and, in the case of a continuous game, satisfies second order conditions, the existence of an equilibrium is established.

2.2. *Solving the DP*

Estimating structural parameters that are consistent with dynamic behavior, as discussed above, can be computationally costly. At each step of the parameter search, the corresponding DP must be re-solved. Solving the DP for a model that "realistically" captures key patterns in the data is typically intractable analytically, requiring numerical methods. To illustrate, we first discuss some basic numerical methods below. We then discuss some recent advances that have helped improve solving the DP for specific empirical problems.

The solution of a dynamic programming problem involves several computational considerations. In particular, one has to choose a method by which the value and policy functions are approximated and stored in the computer memory. Furthermore, an integration method has to be selected (see Judd, 1998; Benitez-Silva et al., 2000). One leading method is to discretize the state space, and then represent the function using its values at the selected grid points. Function values outside the grid can be obtained using interpolation or extrapolation methods. Alternatively, instead of choosing such a non-parametric approximation method, a function can be approximated parametrically using a linear combination of basis functions, such as orthogonal polynomials. In order to calculate the integral in the Bellman equation, quadrature methods or MC methods can be used. Typically, the solution of a DP is computationally challenging. In particular, the CPU time to calculate a function value increases exponentially in the dimension of the state space, which is the well known "curse of dimensionality".[2]

For illustrative purposes, we summarize how one would go about solving the DP by discretizing the state space.[3] The value functions are represented on a grid $\mathcal{G} = \{g^i | i = 1, \ldots, G\}$. This grid is constructed by first discretizing each axis of the state space, Ω, into the points $g_{j1} < g_{j2} < \cdots < g_{jK}$, and then collecting all $G = K^J$ resulting J dimensional points. The algorithm takes some initial guess of the strategy profile, $\sigma^0 = (\sigma_1^0, \ldots, \sigma_J^0)$, and then proceeds according to the following steps:

1. For the strategy profile σ^n, calculate the corresponding value functions V_j^n for each of the J firms. These value function are defined by the Bellman Eq. (4), where the maximization on the right hand side is not actually carried out, but instead the current guess of the strategy profile σ^n is used.

2. If $n > 0$, check whether the value functions and policies satisfy the convergence criteria, $\|V_j^n - V_j^{n-1}\| < \varepsilon_V$ and $\|\sigma_j^n - \sigma_j^{n-1}\| < \varepsilon_\sigma$. If so, stop.
3. Update each firm's strategy from the Bellman Eq. (4). In contrast to Step 1, the maximization on the right hand side is now carried out. Denote the resulting new policies by σ^{n+1}, and return to Step 1.

In empirical work, this type of iterative procedure would need to be repeated during each stage of the parameter estimation procedure. We next discuss some recent approaches that have avoided the need to solve the DP and, hence, reduce the computational burden while still recovering parameters that are consistent with rational forward-looking behavior.

We begin with a discussion of single-agent models, such as the dynamic consumer brand choice problem. Heterogeneity in consumer tastes exacerbates the computational problems raised above. Not only must the DP be re-solved at each stage of the parameter search, the DP must also be solved for each consumer type. Recent advances have helped accommodate richer distributions of consumer types. Hartmann (2004) uses an importance-sampling and change-of-variables approach proposed by Ackerberg (2003). The change-of-variables allows the problem to be re-parameterized in such a way that the DP can be solved once for each individual type. Since the DP need not be re-solved during the parameter search, one can feasibly accommodate a richer distribution of heterogeneity. Similarly, Imai et al. (2004) propose a novel approach that completely avoids the need for numerically solving the DP and, in principle, avoids the "curse of dimensionality". They re-cast the problem as part of a Bayesian Markov Chain Monte Carlo (MCMC) algorithm that simultaneously solves the DP and estimates the model parameters. The iterations of the Bellman equation are treated as successive stages of a Markov Chain. The approach is computationally parsimonious because the DP only needs to be solved for states that are, statistically speaking, "likely" to be realized.

In the context of dynamic games, there is still very little empirical work that truly "solves" for the dynamic equilibrium policies of firms selling differentiated products. The main problem is that the dimension of the state space will typically grow proportionately to the number of products (i.e. each product has a separate control). In a few special cases where the dynamic behavior arise only on the supply side, researchers have proceeded in two stages. In stage one, the demand system is estimated empirically using conventional methods. In stage two, the corresponding firm strategies are computed numerically conditional on the estimated demand parameters (e.g. Benkard, 2004; Dubé et al., 2004; Nair, 2004; Ching, 2004).

Several papers have proposed calculating or simulating the value function (up to unknown parameters) implied by transition rules and decision rules estimated directly from the data in a first stage (e.g. Hotz and Miller, 1993; Aguirregabiria and Mira, 2002; Bajari et al., 2004). These procedures rule out the unobserved heterogeneity discussed earlier, but can estimate dynamic games or single-agent decision processes that otherwise suffer from the curse of dimensionality. The approach of Bajari et al. (2004) resolves problems of multiple equilibria by directly recovering equilibrium beliefs from the data. An implication of these methods is that the full set of restrictions implied by a theoretical model do not have to be imposed during estimation in order to obtain consistent estimates of model parameters. Bajari and Fox (2004) use a similar idea to derive a consistent estimator for static discrete choice models with potentially millions of choices. With a large number of choices, it is computationally intractable to compute many standard discrete choice estimators found in the literature. Bajari and Fox's estimator considers only a subset of choices while retaining consistency for the underlying models with possibly millions of choices.

In a related literature, Berry and Pakes (2000) propose an alternative estimator for the structural parameters of a dynamic model that avoids the need for iteratively solving the Bellman Eq. (4). Instead, the first-order conditions of (4) are used to characterize the optimality conditions with the assumption that agents have rational expectations. As in Bajari et al. (2004), the approach resolves problems of multiple equilibria by directly recovering equilibrium beliefs from the data. Chan and Seetheraman (2004) use this approach to estimate price-cost margins based on observed shelf-price data. They hypothesize that retail mark-ups derive from a forward-looking dynamic pricing policy due to state-dependence in consumer demand. With K consumer "types" and J products, the DP would have a state space with at least $J * K$ dimensions which, for typical product markets, would be infeasible to solve (the curse of dimensionality). For this reason, in a related paper, Che et al. (2004) approximate the dynamic pricing policies by assuming firms solve a finite-planning horizon problem[4]. In contrast, while Chan and Seetheraman (2004) do not explicitly solve the DP, they use the approach of Berry and Pakes (2000) and, hence, they do estimate structural parameters consistent with MPE.

One of the key computational burdens for estimating structural parameters for dynamic models is the need to re-solve the DP at each stage of estimation procedure. The discussion above suggests a number of approaches that have been used for estimating structural parameters that are consistent with the optimality conditions of the DP, without the need for solving it. While these approaches are effective for estimation, one must still formally solve the DP for policy simulations. This limitation is less problematic as, for policy simulation, the DP only needs to be solved once. Recent developments in computational methods (Pakes and McGuire, 2001; Doraszelski and Judd, 2004) will gradually address these concerns. A second area for future research is the analysis of markets in which both consumers and firms are forward-looking. Ignoring the two-sided dynamics in such markets could lead to mis-interpretation of the estimated structural parameters.

3. Entry and Product "Type" Choice

In this section, we focus on empirical models that account for the endogenous choice of variables other than price. Since we already discussed advertising in the section on dynamics, we will discuss specifically the endogenous entry and product attribute decisions.

Early conventional wisdom in industrial organization (e.g. Bain, 1962) rationalized that exogenous market structures dictate firm conduct, which in turn determines profits: the "structure-conduct-performance" paradigm. In this light, one need only identify market structure characteristics, such as concentration, to draw inferences about firms' strategic behavior and profitability in a market. The game-theoretic revolution of industrial organization has provided numerous theoretical counter-arguments. Under a broad class of models that jointly consider entry, product location choice and competition, the intensity of competition can dictate the extent of entry and, hence, market structure (Shaked and Sutton, 1987; Sutton, 1991). If margins are sufficiently high to cover fixed (and sunk) costs, firms will enter a market and select their product "type." Understanding product type choices will be influential in understanding the competitive interactions between differentiated firms. The nature of demand will influence the total number of firms and the relative product locations chosen, which in turn influence the realized price-cost margins. In this respect, causal variables for the intensity of competition in a market (e.g. demand-shifting variables) can be informative about the formation of market structures and, hence, profits. Hence, the analysis of entry and product positioning decisions are of substantive interest for understanding the emergence of long-run market structures.

Bresnahan and Reiss (1991a) provide one of the earliest structural analyses of entry. In the context of homogeneous goods markets they investigate the relationship between profits and the equilibrium number of firms in a market (see also Berry, 1992 who studied entry by airlines across US airports). Since market outcomes such as prices, sales and profits are not observed, a reduced-form approach is used to characterize the profit function in terms of demand-shifting market characteristics. A multi-agent qualitative response formulation estimates thresholds, based on market characteristics, to determine the probability of observing a specific market structure (e.g. monopoly, duopoly etc.). They find that increases in demand intensify competition by stimulating more entry and reducing margins.

In general, games of firm entry decisions are hampered by the potential existence of multiple equilibria. Consider a simple (2×2) entry game. Suppose a firm $i = 1, 2$ has entered a market m and has a profit function:

$$\pi_{im} = \alpha + \beta X_m + \varepsilon_{im}$$

where X_m are demand-shifting variables. All firms are assumed to have identical profits except for an idiosyncratic mean-zero shock, ε_{im}. Firm i enters the market if it earns non-negative profits:

$$\alpha + \beta X_m + \varepsilon_{im} \geq 0.$$

We can denote the pay-off of firm i as:

$$y_i = 1(\Delta_i y_{-i} + \varepsilon_i \geq 0)$$

where Δ_i is the change in firm i's profits when the other firm enters. If $-\Delta_i \geq \varepsilon_i \geq 0$, then either firm could enter the market as a monopolist. Hence, this entry game has a unique prediction for the total number of firms who enter the market, but it may have multiple equilibria in the identities of the firms who enter.

Multiple equilibria in both the number and identities of entering firms becomes even more problematic in more sophisticated environments with heterogeneous firms (e.g. product-differentiated firms). The intensity of competition between firms will depend on their relative locations decisions (i.e. in an "attribute" space), potentially generating multiple equilibria. In general, strong assumptions are necessary for point identification of the parameters of interest in environments with firm heterogeneity. For example, firm's entry costs are assumed to be independent of the set of firms that enter the market. Symmetry is often also imposed so that firms impact one-anothers' profit functions symmetrically. These conditions typically ensure uniqueness in the predicted number of firms in a market (e.g. Bresnahan and Reiss, 1991b). Berry (1992) allows for heterogeneity in firms' costs, but assumes that firms enter sequentially to ensure the uniqueness of the equilibrium. For simple discrete games with multiple equilibria in the spirit of those discussed above, Tamer (2003) and Ciliberto and Tamer (2004) propose estimators that permit point identification, in the former, and the testing of candidate equilibrium selection criteria, in the latter.

More closely-related to Sutton (1991), recent literature has extended the study of entry decisions to accommodate product location decisions (e.g. Mazzeo, 2002; Seim, 2004). Modeling product "type" choices raises computational problems because firms need to calculate their profits based on conjectures they have about competitors's reactions under each possible location configuration. Mazzeo (2002) extends the work of Bresnahan and Reiss (1991a) and Berry (1992) to accommodate entry and product "type" choice (service quality of hotels). As discussed above, symmetry is imposed to resolve problems of multiple equilibria. The model is also restricted such that only two levels of service quality are permitted and only three firms of a given quality type can enter a market, constraining the outcome space to fifteen candidate values. As such, Mazzeo can evaluate the Nash equilibrium analytically.

More generally, such analytical solutions are infeasible. Seim (2004) looks at the entry and geographic location decisions of video rental retail outlets. She proposes a way of dealing with the dimensionality problem. It is computationally infeasible to compute all the possible geographic configurations of firms, preventing the direct computation of the Nash equilibrium in product locations. Seim resolves the computational problem by adding an additional layer of uncertainty. Each firm is assumed to have private information about their costs and potential profits. In the corresponding Bayesian Nash equilibrium, firms have no precise conjectures on the locations of their competitors, but only on the competitors' likelihoods of entering a specific location. This outcome simplifies the numerical computation of the location equilibrium in comparison with a game of complete information. The uncertainty thus reduces the dimension of the optimization problem.

Most of the literature has focused its attention on product location choice and entry, mainly due to a lack of data on market outcomes such as prices and sales. Draganska et al. (2004) extend the approach of Seim (2004) by incorporating product market competition into the analysis using scanner data that includes prices and sales. They also broaden the scope of product location choices by considering a more abstract "characteristics" space (i.e. flavors in the ice cream market). Empirically estimating the parameters of a model of supply and demand with endogenous product positioning provides a more complete characterization of the long-run equilibrium in a consumer product market. When conducting policy simulations, one can investigate the implications not only for prices, but also for product variety supplied.

Using similar techniques, Crawford and Shum (2004) directly address the product positioning problem in the cable television industry.[5] By modeling structurally the formulation of a non-linear pricing structure, prices and product quality are endogenous in their framework. They use a novel approach to computing the optimal pricing structure. Using the recent insight of Rochet and Stole (2001), the non-linear pricing problem is recast as a generalized one-dimensional screening model with random participation. In this setting, consumers have private information about their tastes for product attributes. The monopolist only knows the distribution of tastes and, hence, offers a range of qualities with corresponding prices to induce consumers to self-select. The advantage of this formulation is that the screening literature has a well-established set of analytical techniques for finding equilibria. From a practical point of view, ignoring the quality choice decision could lead to endogeneity bias in the estimated demand elasticities. Substantively, Crawford and Shum (2004) use the model estimates to measure empirically the degree of quality distortion that occurs in the provision of basic cable services. An interesting extension of this work would be to apply it to competitive environments and to investigate the impact of competition on the amount of screening that emerges along with the corresponding welfare implications for consumers (e.g. Villas-Boas and Schmidt-Mohr, 1999; Stole, 2004).

Related to the discussion of product positioning is the issue of new product launches. Much of the structural literature on new products has taken a static approach. The timing of the introduction of the new product is treated as exogenous and structural parameters are estimated to describe the impact on competition, profits and consumer welfare (e.g. Hausman, 1997; Kadiyali et al., 1999; Petrin, 2002). Typically, this static approach is dictated by the lack of variation in characteristics of new products, mainly due to a general lack of observed product launches.

Hitsch (2004) investigates how product launch and exit decisions should be made under uncertainty about product demand and hence the profitability of a new product. He considers a firm that learns whether a product is profitable or not from observed product sales. Conditional on the current information, the firm keeps the product in the market or decides to scrap it. Formally, this is a sequential experimentation problem in statistical decision theory, which can generally only be solved using dynamic programming techniques. In Hitsch's application to the U.S. breakfast cereal industry, the model predicts that under some demand uncertainty firms should launch a new product even if they expect that it is unprofitable. Hence, it can be rational to incur a high product 'failure' rate in order to find an occasional profitable product among the unprofitable ones.

Formally modeling the dynamics associated with the timing of new product launches is a formidable task. Formally, Hitsch's model can be thought of as a sequential experimentation problem in statistical decision theory, which can generally only be solved using dynamic programming techniques. Einav (2003) studies the timing of movie release dates as a strategic game. The game is similar in spirit to the location-choice problem of Seim (2004), except that firms are assumed to move sequentially. The heterogeneity associated with sequential moves ensures uniqueness of equilibrium.

In the same vein, Economides et al. (2004) evaluate the welfare implications of post-deregulation entry into local phone service by carriers who previously only provided long distance services. In this case, treating the timing of entry as exogenous is reasonable since it was the outcome of a government policy change (i.e. de-regulation). A second advantage of this specific context is that incumbents' prices can, somewhat reasonably, be treated as exogenous as they are constrained by regulation. Hence, unlike previous work (e.g. Hausman, 1997), the price equilibrium does not need to be re-solved under the counter-factual "no-entry" scenario. These simplifications enable the authors to focus more on the complexities of consumer demand for phone service. Consumer demand is inherently discrete-continuous as they must choose both a calling plan and the number of minutes to consume. Hence, they propose a model of demand over multi-part tariff structures. Consumers' discrete choices are influenced by perceived quality differences in carriers' services and detailed household level data allows identification of differences in perceived quality across firms and market regions.

During the past decade, the empirical analysis of market structure has seen a strong resurgence. Of specific interest has been the study of firm entry, product differentiation and the intensity of competition in an industry. These factors can all be integrated to learn about the formation of long-run market structures. Developing adequate structural approaches has required resolving computational challenges as well as managing the tendency for multiple equilibria to arise in more "realistic" models with heterogeneous firms. Finally, the extant literature has developed structural tests for the nature and the intensity of competition taking firm entry and product "types" as given (e.g. Kadiyali, 1996; Sudhir, 2001). Linking the literature testing firm conduct back to entry and product positioning decisions would be an interesting area for future research.

4. Conclusions

We have provided a brief overview of two recent research areas in the structural modeling of markets for consumer goods, dynamics and endogenous entry and product positioning. Both areas present considerable new opportunities for research regarding long-run marketing problems in contrast to the extant focus on short-run marketing mix decisions. However, research in these areas faces a number of complicated computational and methodological issues. We have discussed these issues in some detail, with a focus on specific empirical applications that clarify suggested remedies.

Addressing dynamics by modeling the forward-looking behavior of consumers and firms in a structural framework permits a much richer understanding of their behavior. Perhaps even more important, there are systematic patterns in our typical consumer databases that simply cannot be captured by static models. A notable example is the pattern of temporary price cuts that arise in most repeat-purchase retail environments. Static approximations, such as the Bertrand Nash equilibrium, relegate the incidence of such price-cuts to random disturbance, throwing away one of the primary sources of price variation. The development of more elaborate dynamic programming techniques should help us obtain insights about the reasons for the existence of these patterns. New techniques seek to ameliorate computational needs by avoiding the computationally intensive process of iteratively solving a dynamic program at each stage of the parameter estimation. Advances of this type will make it feasible to estimate richer dynamic structural models of firm and consumer behavior.

Addressing strategic entry and product positioning decisions broadens our understanding of marketing new products with a more long-run perspective. The growing empirical literature on market structure has validated game-theoretic predictions regarding entry and competition, permanently changing the conventional wisdom in industrial organization.

Gradually, the literature has accommodated more complex analyses linking firm's entry and product positioning decisions to the intensity of competition in a market. However, these more elaborate models are routinely hampered by a multiplicity of equilbria. Frequently, specific parametric restrictions may be required to ensure the uniqueness of the predicted equilibrium market structure.

The more recent literature that models product "type" choice faces additional computational problems due to the large number of possible product configurations. In the research surveyed above, the nature of product differentiation ranged from geographic locations (video stores) and outlet qualities (hotels), to product quality configurations (Cable TV packages and local phone service subscriptions) and general product-line decisions (Ice Cream and RTE Cereals). Often, moving to games of incomplete information can be helpful in the computation of product location equilibrium. Besides the contribution to the literature on market structure, endogenizing product location and quality choices also contributes to the literature estimating differentiated product demand systems. Researchers have readily-accepted the potential for price endogeneity to bias parameter estimates in estimating demand systems. The endogeneity of product positioning could generate analogous problems.

Looking forward, an important next step in this literature will be to address the challenges raised in the work surveyed here. For example, can empirical models be developed that capture the dynamics that arise in markets with inter-temporal patterns of product entry and exit? In such instances, the role of history and firm asymmetries could help resolve some of the problems with multiple equilibria. Furthermore, despite the fact that most markets involve multi-dimensional product characteristics spaces and aggressive competition, existing applications of screening models to endogenize product characteristics have limited the number of characteristics and firms considered (Stole, 2004). Are there reasonable simplifications on the underlying structure of preferences and costs that yield tractable equilibria?

Finally, the extension of structural modeling to dynamic environments places fundamentally greater demands on the data required to study strategic choices accurately. Data at the daily level may be needed to understand consumer behavior in some cases, as in the analysis of the effects of advertising exposure. Examples of the data used in the research surveyed above included daily individual choice of golf club, daily household choice of food products in supermarkets, and weekly firm-level choices of advertising and prices levels by geographic area. In each case, the dynamic model was necessary to capture a key pattern in the data that could not be addressed by a static model. More generally, the estimation of dynamic models of competitive interaction would appear to require long histories on firm interaction, ideally from separate markets. While obtaining such data may be a significant hurdle, the empirical tools now being developed (faster computational algorithms and two-step estimators that avoid the need to solve the DP) suggest the potential to model accurately the important strategic questions of contemporary interest to firms.

Notes

1. We restrict our attention to pure strategies. The numerical solution of a more general model with mixed strategies would be substantially more difficult.

2. In a model with continuous states, we typically discretize the range of values each state can take on and evaluate the value function at each point. Adding more states increases the number of value function calculations exponentially.
3. Rust (1995) and Judd (1998) provide overviews of dynamic programming techniques.
4. While this approach does not yield a formal MPE per se (i.e. the assumed behavior is not fully-rational), it is suggested as a practical decision-support system for firms to capture the spirit of forward-looking behavior without addressing an intractable dynamic programming problem.
5. From an econometric perspective, Miravate (2002) demostrates that the information in such nonlinear pricing contracts can help better estimate the distribution of consumer willingness to pay in a monopoly situation; Miravate and Roller (2004) demonstrate that this is true in the context of a duopoly as well.

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