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Structural analysis of competitive behavior: New Empirical Industrial Organization methods in marketing

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Abstract

The impact of a firm's strategic marketing mix choices on profitability can be evaluated by understanding the impact of those choices on consumer demand for the firm's products and on the firm's costs. Additionally, a firm's strategic marketing mix choices, and its demand and costs can be affected by rival firms' strategic choices. Therefore, to understand the effects of choice of marketing mix on profitability, we have to understand its effects on demand, cost and competitor reactions. The effects of choices of marketing mix on consumer demand have been analyzed in great depth in marketing, but research on the strategic reactions of competitors to such choices have been far more limited. The New Empirical Industrial Organization (NEIO) framework provides us with a source of methods that has potential to substantially add to our insights about competitive interactions among firms.

In this paper, we first discuss a simple NEIO model to illustrate the basic methodology. We then discuss the contributions of this literature to our knowledge of competitive marketing strategy. In the process, we discuss methodological extensions of the basic model that are needed to model the institutional realities of specific markets. We also summarize how the existing literature has evolved, and provide our view of where the literature might profitably proceed from here. In particular, we discuss how future methodological innovations in the dynamics of competition, discrete strategy choice, and asymmetric information estimation will enable wider application of this methodology to competitive marketing strategy issues. The main advantage of NEIO studies is that they provide greater understanding of the competitive behavior in specific markets or industries compared to cross-sectional studies across industries. Bountiful opportunities exist for additional studies that focus on similar phenomena in different markets to draw generalizable conclusions from this line of research.

Keywords: Structural models; Competition; Strategic behavior; New empirical industrial organization

1. Introduction

The impact of a firm's strategic marketing mix choices on profitability can be evaluated by understanding the impact of those choices on consumer demand for the firm's products and on the firm's costs. Additionally, a firm's strategic marketing mix choices, and its demand and costs can be affected by rival firms' strategic choices. Therefore, to understand the effects of choice of marketing mix on profitability, we have to understand its effects on demand, cost and competitor reactions. The effects of choices of marketing mix on consumer demand

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have been analyzed in great depth in marketing, but research on the strategic reactions of competitors to such choices have been far more limited.

There is a rich tradition of empirical research in marketing strategy beginning in the 1950s that examines the impact of cost and competitive characteristics of a market on the profitability of firms. This empirical tradition following the structure–conduct–performance (hereafter referred to as SCP) paradigm of empirical industrial organization uses cross-sectional data across industries to find empirical regularities across industries. Many of these studies in marketing have used the Profit Impact of Marketing Strategies (PIMS) data (see Buzzell and Gale, 1987 for a survey). These studies have provided valuable insights about the empirical regularities of relationships between marketing mix choices like advertising, cost components including R&D etc., and profits of firms.

Beginning in the late seventies, advances in game theory have led to a large amount of theoretical research analyzing strategic issues in the context of competition between firms, firms and channel members, firms and their advertising agencies, etc. (For a review, see Moorthy, 1993.) This research convinced empirical researchers that market outcomes (i.e., firms' strategic marketing mix choices and the resulting sales, etc.) and profitability are not merely a function of the broad structural characteristics used in SCP studies. Rather, these market outcomes and profitability are affected by specific industry and firm specific demand and cost characteristics that are difficult to model within the SCP framework of cross-industry analysis. A consequence of these insights has been the birth of the "New Empirical Industrial Organization" literature (henceforth referred to as NEIO; for a review see Bresnahan, 1989). This literature incorporates more industry- and firm-specific details in modeling demand, cost, and competition as steps in analyzing the relationship between marketing mix and profits. Therefore, this approach should be seen as the next step in the stream of empirical research in marketing strategy after the SCP literature. The goal of this paper is to review this literature and provide an agenda for future work.

The NEIO approach involves the development and estimation of structural econometric models of strategic, competitive behavior by firms. By a structural model, we mean a model where firms' choices are based on some kind of optimizing behavior (usually profit maximization). In this respect these models are similar to structural models of consumer choice, which are built on the assumption of utility maximization behavior of consumers. Where they differ is that NEIO structural models are strategic while structural models of consumer choice are non-strategic. Consumer models are non-strategic because one consumer's choice has no impact on another consumer's choice and therefore, these choices can be assumed to be independent. In contrast, NEIO models of firms need to account for the interdependency of firm choices: a firm's choice will cause a reaction from its competitor. This modeling of strategic behavior is the key difference between structural models of consumer choice and structural models of firm choice.

This difference between consumer choice and firm choice has two econometric implications. The first issue is simultaneity. Firms make their strategic marketing mix choices simultaneously. That is, any one firm's choice is a function of its rivals' choice, and rivals' choice a function of this firm's choices. Further, firm choices affect demand and demand characteristics affect firm choices. Therefore, from an estimation viewpoint, the realized demand and the firm's strategic choices are simultaneous. The simultaneity is accounted for by estimating the demand equations and the choice equations of firms as a system of simultaneous equations. The second issue is endogeneity. In consumer choice models, it is assumed that each individual's choice by itself has no effect on the firm's choices such as prices and promotions in consumer choice studies; therefore, firm's decisions are treated as exogenous. However, in a structural model of firm choice where separate equations for firms' choices are estimated, the choices have to be treated as endogenous. We therefore have to use instruments for these choice variables to account for the endogeneity.

A structural model of competitive interaction provides at least four benefits, which we will elaborate on in various parts of the paper.

(1) *Theory testing*: The structural approach provides an opportunity to empirically compare and test alternative theories of strategic behavior. A better

fitting model can be deemed to be more descriptive of the phenomenon.

(2) *Ease of interpretation*: Structural models are linked to a behavioral theory (for example, profit maximization) of firms; hence, the estimated parameters have economic or behavioral meanings that can be interpreted easily. This advantage is parallel to uncovering the parameters of the consumer utility function in consumer choice studies.

(3) *"What-if" analysis*: Estimated parameters of a structural model are invariant to policy changes (i.e., they are not subject to the well-known problems of the Lucas critique). Managers can therefore use these estimates to perform "what-if" analysis to understand what effect their actions will have on the market.

(4) *Decomposing the determinants of market power and profitability*: Many studies in NEIO have focussed on measuring market power. The Lerner index[1] is a good measure of market power and serves as a measure of the profitability of firms. Structural NEIO models decompose the sources of market power (profitability) into components associated with demand structure, cost structure and competitive interaction. Hence, differences in profitability among firms in an industry can be attributed to consumer preferences (demand structure), efficiency (cost advantages), and anti-competitive conduct (tacitly cooperative behavior). Armed with this description about the structure of their market, each firm can figure out how they can use the marketing mix to most efficiently boost their market power. A similar analysis can be done for better understanding the determinants of profitability in closely related markets (for e.g., different geographical markets within the same industry).

The rest of this paper is organized as follows. In Section 2, we compare other modeling traditions in empirical industrial organization to the NEIO approach. We use a simple example to illustrate the principles of NEIO modeling in Section 3. We review the literature and its contributions in Section 4. In the process, we discuss the current limitations in the literature and suggest several methodological extensions to the basic model that are needed to represent specific institutional realities. We conclude the paper with a summary in Section 5.

2. Modeling traditions in Empirical Industrial Organization

We classify the modeling traditions in Empirical Industrial Organization in Fig. 1 to provide an overview of various methods and their differences. The new empirical industrial organization paradigm is primarily focused on the analysis of firm behavior in a specific market or closely related markets. This is in contrast to the previously dominant empirical paradigm in the field of industrial organization, the structure–conduct–performance or SCP paradigm. We briefly review the SCP paradigm, the reduced-form hypothesis testing approach and the reaction function approaches, before discussing in detail the New Empirical Industrial Organization paradigm (or structural analysis of strategic behavior).

2.1. The structure–conduct–performance paradigm

Until the early eighties, empirical analysis of firm behavior in industrial organization was based on the structure–conduct–performance (SCP) paradigm following the seminal work by Bain (1951). The SCP paradigm is illustrated in Fig. 2.

The industry competitive structure is measured by such factors related to both demand- and cost-side primitives; common measures include concentration, growth, scale economies, buyer and supplier power, barriers to entry, and degree of product differentiation. Industry conduct is defined by the factors related to competitive behavior as choices of market-

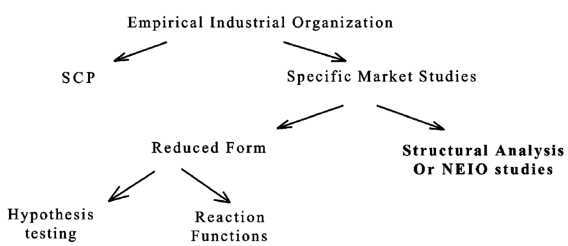

Fig. 1. A taxonomy of Empirical Industrial Organization modeling approaches.

[1] Lerner index = (price − marginal cost)/price.

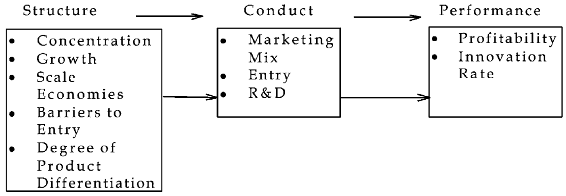

Fig. 2. Structure conduct performance (SCP) approach.

ing mix, decisions to enter a market, R&D investment. Industry performance is measured by profitability, rate of innovation, etc. The SCP paradigm states that industry structure drives industry conduct, which in turn drives industry performance. Much of the analysis of firm behavior in marketing and strategy using PIMS data was also based on this paradigm (see Buzzell and Gale, 1987 for a comprehensive review). To marketers and business strategy researchers, the structure- and conduct-based determinants of profitability were of great interest, because they could provide managers with guidelines on what structural characteristics make markets profitable and what kinds of conduct are conducive to profitability. For example, whether managers should pursue market share for higher profits has been one of the most controversial questions in this literature (for a meta analysis, see Szymansky et al., 1993). Therefore, the literature using SCP paradigm has provided many important insights on empirical regularities across markets and within markets.

There are some conceptual, methodological and data issues with this literature. One conceptual concern is the inability to effectively capture the heterogeneity in the structural characteristics and the resulting optimum marketing mix strategies of firms across industries, and across firms within a given industry. Typically, studies in this literature pool cross-sectional data across disparate industries in estimating the SCP relationships. To address this criticism, researchers have used econometric methods to control for heterogeneity across the population. One technique employed in the literature is to run separate regressions for different homogeneous subgroups of firms (Prescott et al., 1986). Another approach is to allow fixed effects for firms; this approach has exploited the panel nature of PIMS data (Boulding and Staelin, 1990, 1993). Controlling for heterogeneity in this fashion addresses the econometric problem.

This issue of heterogeneity is, however, deeper than a debate about the appropriateness of econometric methodology. The relevant issue is that the heterogeneity among industries is more than what can be captured by the structural variables used in SCP studies. Markets differ in more fundamental ways within the industry, such as differences in cost and demand structures among firms and order of moves by different competitors. Game theory shows that these kinds of market-specific characteristics have a substantial impact on market outcomes. This implies that the structural variables used in SCP studies are not sufficient statistics to account for the vast heterogeneity across industries and the resulting market outcomes. Such heterogeneity can best be accounted for by carefully modeling the details of a specific market. Clearly there is a trade-off between depth and breadth. SCP studies by virtue of their breadth of analysis across industries provide generalizable insights across industries. In contrast, since NEIO studies are case studies, they do not lend themselves to easy generalizations, though there is greater depth in the observed relationships. Generalizability in NEIO should come through replication of results in multiple case studies across similar markets. We discuss this tradeoff in more detail in Section 6.

A major methodological issue with the SCP paradigm is the non-exogeneity of structural variables. That is, the structural characteristics that determine conduct are not truly exogenous. While structure has an impact on conduct, conduct in turn can affect structure. Consider these relationships between conduct and structure: marketing strategies like choice of product characteristics and advertising affect product differentiation; barriers to entry are a function of the product positioning and pricing behavior of incumbents; R&D investments affect the cost structure of firms in an industry. As Wind and Lilien (1993) say, "The PIMS results are norms; therefore, the equations do not have a causal interpretation. Although it is tempting to predict the consequences on profitability of changes in the independent variables of the (PAR) model, it is not reasonable to do so." The estimated relationships in SCP models are therefore correlational, not causal. One solution to this endogeneity issue is to use instrumental variables for the endogenous structural variables. However, good instruments are hard to find. A more complete solution would be to model the process by which these endogenous structural variables are chosen by firms, or in other words, follow the structural estimation route of NEIO studies.

A third issue with the SCP literature is the type of data used in several of these studies. Researchers have typically used three- or four-digit SIC industry codes to define industries in which to study SCP relationships. These code-based industry definitions may be too narrow sometimes (e.g., aspartame should be included in the competitive set when examining the market for sugar), and too broad sometimes (e.g., the market for instant photography is quite distinct from the market for regular developing photographic film). Of course, industry definitions are critical in the construction of structural variables such as concentration and market share, and in estimating marketing mix–profitability relationships. PIMS studies are more careful in this regard, because they analyze competition at the SBU level. Nevertheless, even SBUs usually have product lines targeted to different segments. The appropriate structural measures would be at the segment level, but SCP studies usually would find it hard to find such detailed data across a broad cross-section of industries. Sudhir's (2001a) analysis is an illustration of how a segment level analysis of the auto market provides more detailed insights than would be possible with an aggregate level analysis.

A more vexing data problem is the measurement of costs. Costs are crucial in the construction of market performance variables such as profitability. Many studies have used accounting costs for measuring profits. But accounting costs are usually average costs and not correlated with marginal (economic) costs. Similarly, accounting profits are not the same as economic profits. Therefore, conclusions of SCP using accounting data can be suspect.

Managerially, while cross-industry observations no doubt provide some guidance in selecting optimum marketing mix, managers are often interested in the details of their own industry because these provide invaluable inputs in to strategic decisions. Consider the study of Suslow (1986), where a demand-and-supply model of aluminum is estimated to understand where and why Alcoa, the leading aluminum producer, makes profits. Suslow carefully includes the recycled aluminum suppliers in defining the industry. She finds that despite the presence of these additional suppliers in the industry, Alcoa has significant market power because recycled aluminum is viewed as inferior to primary aluminum. Nevertheless, recycled aluminum does act as a brake on the pricing power of Alcoa for primary aluminum. Since the quantity of recycled aluminum in a market is a lagged function (it takes several years for primary aluminum to become recycled aluminum) of the primary aluminum produced by Alcoa, Alcoa's current pricing policies will have an impact on its future market power. Managers can therefore use Suslow's estimates of demand, supply and costs to determine an optimal long-term pricing policy. Such an exercise would be impossible to do using a standard SCP approach.

Summarizing, SCP studies are unable to adequately capture heterogeneity across industries and firms in the marketing mix–profitability relationships. Additionally, there are econometric issues of endogeneity of some of the explanatory variables in the SCP paradigm. Last, there also appear to be serious data issues with these studies. Therefore, the results of the SCP studies should be seen as providing us stylized facts of marketing mix–profitability relationship, rather than giving us insights in to why and how this relationship is structured.[2] Further, since the estimates of a structural approach are specific to a market, they are managerially useful in determining the optimal marketing mix.

2.2. Comparative statics or hypothesis testing

A reduced-form method is to test comparative statics generated from structural game-theoretic models with regressions between structural characteristics and industry conduct. The crucial difference between the SCP approach and the reduced-form hypothesis testing lies in the fact that hypothesis testing is done on a cross-section of closely related markets or using time series data on a single market. Therefore, while SCP regressions provide correla-

[2] For a critique of the SCP approach and also a summary of the main insights gained from this stream of research, refer to Schmalensee (1989).

tional rather than causal relationships, these regressions give causal relationships resulting from strategic competitive optimization resulting from game-theoretic behavior models. But unlike structural NEIO studies, these reduced-form approaches do not decompose demand, cost and competitive effects on firm strategic choices.

We illustrate the principles underlying reduced-form model-based hypothesis testing with a paper by Agrawal and Lal (1995). This paper tests several hypotheses about the role of royalty and monitoring arrangements in a franchising system. Based on the comparative statics in Lal (1990) and Agrawal and Lal (1995), Agrawal and Lal regress brand name investments, service levels and monitoring frequency against royalty rate and monitoring costs. Their theoretical models guide their expectations on the signs of these effects. For example, a higher monitoring cost should lead to lower monitoring frequency. Based on the evidence from these regressions, they argue that the model of Lal (1990) and its extension in Agrawal and Lal (1995) are consistent with the data.

An issue with the above hypothesis-testing approach is that reduced-form analyses provide no policy invariant descriptions of specific markets. That is, since we do not obtain demand, cost and competition primitives from the estimation process, the estimates cannot be used in an optimizing model for managers making decisions. The advantage is that they place very limited structure either on demand- or supply-side and hence are useful in exploratory empirical analysis of competitive behavior.

2.3. Reaction function studies

The reaction function approach is another reduced-form method that measures how firms react to competitors within a particular industry by regressing a firm's marketing mix against other elements of its own marketing mix and those of its competitors (including lagged values). The pioneering work in this area was by Lambin et al. (1975) and Hanssens (1980). Leeflang and Wittink (1996) use this technique to analyze pricing and promotional competitive behavior using store level scanner data. They provide a very useful link to structural models because they estimate both market share equations (demand-side of the market) as well as reaction functions (supply- or competitive-side of the market). Unlike the hypothesis testing described in Section 2.2 above, these regressions do not result from any direct optimization behavior. But unlike the SCP literature, reaction functions are always at the firm level within an industry and hence, account for the industry- and firm-level heterogeneity in marketing mix–profitability relationships.

Though the reaction function technique is useful as a description of competitive reactions, it does not provide insight into the underlying reasons for the observed reactions. This is because the reactions are not based on primitives of demand and cost characteristics facing firms and the nature of the equilibrium between firms. For example, if reaction functions show that firms' optimal choices are very responsive to their rivals' choices, is this because firms have very similar cost conditions and these costs are changing over the time period studied? Or is it because competition is very intensive and hence, there is price matching every time? Or is it because firms collude, but demand shifts cause price shifts? Such questions can be answered in a structural approach because the reactions are linked to demand, cost and equilibrium characteristics underlying the market.

Nevertheless, the reaction function approach does provide insights into off-equilibrium behavior of firms or to model dynamic interactions, both of which, as we will discuss below, are difficult to model in structural models. Reaction functions can also provide interesting starting points for further empirical work using the NEIO framework.

3. Implementing the NEIO framework: An illustration

In this paper, we will use a simple example to illustrate the workings of a NEIO model. We will also address some issues that a modeler needs to resolve in using these models. Comparing the NEIO models to those discussed in the Section 2, the gains come from two features: (i) these are estimated at the industry level, and more specifically, at the firm level within an industry, and (ii) these are derived from explicit demand and cost, and profit-maximizing primitives.

Because an NEIO model is specified at the level of the industry, the first task is to define the industry. In many studies, the focus has been on the largest two or three firms in an industry or market. Recently, methods have been developed to deal with markets where there are a large number of products.

An NEIO model has three basic ingredients: (1) a demand specification, (2) a cost specification and (3) a specification for competitive interactions.[3] Demand specifications have ranged from simple models such as linear or log-linear demand to flexible nonlinear models such as the logit model with random coefficients to account for heterogeneity of customer preferences. Costs have been specified using a simple constant marginal cost model or as a linear or log-linear function of production cost factors. The specification of competitive interactions needs a little more elaboration. In our illustrative example, we explain three commonly used approaches to model competitive interactions: (1) the menu approach, (2) the conjectural variation approach and (3) the conduct parameter and the weighted profits approach.

Consider a duopoly market with each firm having a differentiated product. The demand for the two products (q_1 and q_2) is as follows.

$$q_1 = a_1 + b_{11} p_1 + b_{12} p_2,$$

$$q_2 = a_2 + b_{21} p_1 + b_{22} p_2.$$

Let the marginal costs of the two products be c_1 and c_2. We will assume each firm chooses prices in such a way as to maximize profits in each period. The profits for firm i is given by,

$$\Pi_i = (p_i - c_i) q_i, \quad i = 1,2.$$

3.1. The menu approach

We derive the first-order conditions under different equilibrium interactions between the two firms and then choose the equilibrium that best fits the data. As an illustration, we derive the econometric estimation models under three equilibria here: Bertrand, Stackelberg leader–follower and collusive equilibrium. In the estimation step, each of these sets of first-order conditions for the different games is estimated separately, and goodness of fit test performed to select the best-fitting one.

3.1.1. The Bertrand equilibrium

In the Bertrand equilibrium, each firm i chooses its prices assuming that competitors do not react to changes in their prices, i.e., they assume $\partial p_j / \partial p_i = 0$. The first-order condition for firm i is:

$$\frac{\partial \Pi_i}{\partial p_i} = (p_i - c_i) \frac{\partial q_i}{\partial p_i} + q_i = 0.$$

For the linear demand equation this is

$$\frac{\partial \Pi_i}{\partial p_i} = (p_i - c_i) b_{ii} + q_i = 0, \quad i = 1,2.$$

These first-order conditions now serve as the supply-side equations describing firm behavior. Note that the equations link demand parameters and costs, i.e., there are cross-equation restrictions.

3.1.2. The Stackelberg leader–follower equilibrium[4]

Let firm 1 be the leader and firm 2 be the follower. In the Stackelberg equilibrium, the follower firm 2 chooses its prices, assuming that the leader does not react to changes in its prices, i.e., it assumes $\partial p_1 / \partial p_2 = 0$. In contrast, the leader firm anticipates the follower's reaction and incorporates

[3] Studies such as those of Panzar and Rosse (1987) and Ashenfelter and Sullivan (1987) have many ingredients of NEIO studies but are not completely structural. Specifically, Panzar and Rosse estimate a reduced-form equation of revenue as a function of factor prices. Although their specification can differentiate between competitive and monopolistic markets, they make an assumption of identical firms in the marketplace. The NEIO framework has shown this assumption to be a restrictive one. Ashenfelter and Sullivan estimate a supply curve for firms in the cigarette industry as function of tax and other cost shifters. However, NEIO studies have demonstrated that to accurately estimate price and quantity movements, demand-side variables have accounted for as well.

[4] An astructural approach to inferring leader–follower behavior is Granger Causality. See Roy et al. (1994) for an illustration.

this into its pricing behavior. The first-order condition for the follower firm 2 is similar to the Bertrand equilibrium.

$$\frac{\partial \Pi_2}{\partial p_2} = (p_2 - c_2) b_{22} + q_2 = 0.$$

Taking the derivative for the first-order condition with respect to p_1, we get

$$\frac{\partial p_2}{\partial p_1} = \frac{-b_{21}}{2b_{22}}.$$

The leader's first-order condition is,

$$(p_1 - c_1)\left(\frac{\partial q_1}{\partial p_1} + \frac{\partial q_1}{\partial p_2}\frac{\partial p_2}{\partial p_1}\right) + q_1 = 0.$$

For the linear demand model,

$$(p_1 - c_1)\left(b_{11} - b_{12}\frac{b_{21}}{2b_{22}}\right) + q_1 = 0.$$

3.1.3. The collusive equilibrium

In the collusive equilibrium, firms choose their prices as if they collusively maximize their total profits. Each firm chooses prices for its products as if it was a monopoly firm selling both differentiated products. The firms' objective is $\Pi = (p_1 - c_1)q_1 + (p_2 - c_2)q_2$. The first-order condition for firm i is given by:

$$\frac{\partial \Pi}{\partial p_i} = (p_i - c_i) b_{ii} + (p_j - c_j) b_{ij} + q_i = 0,$$

$$j \neq i, \quad i = 1,2.$$

3.1.4. Estimation

For each of the models, there are four equations, two describing the demand for each firm and two describing the supply for each firm. In performing the estimation, all these models can be nested in one general model with the following four equations.

$$q_1 = a_1 + b_{11} p_1 + b_{12} p_2,$$

$$q_2 = a_2 + b_{21} p_1 + b_{22} p_2,$$

$$q_1 + \lambda_{11} p_1 + \lambda_{12} p_2 + \delta_{11} c_1 + \delta_{12} c_2 = 0,$$

$$q_2 + \lambda_{21} p_1 + \lambda_{22} p_2 + \delta_{21} c_1 + \delta_{22} c_2 = 0.$$

The restrictions given in Table 1 apply to the parameters when estimating the individual equilibrium models. These models form a simultaneous equation system and a simultaneous equation instrumental variable estimation approach will yield consistent and efficient estimates of the parameters. Three-Stage Least Squares (3SLS), Full Information Maximum Likelihood (FIML), and Generalized Method of Moments (GMM) may be used for estimation.

Table 1
Parameter restrictions for different equilibrium models

Parameter	Bertrand	Leader–follower	Cooperative
λ_{11}	b_{11}	$b_{11} - b_{12}b_{21}/2b_{22}$	b_{11}
λ_{12}	0	0	b_{12}
δ_{11}	$-b_{11}$	$-(b_{11} - b_{12}b_{21}/2b_{22})$	$-b_{11}$
δ_{12}	0	0	$-b_{12}$
λ_{22}	b_{22}	b_{22}	b_{22}
λ_{21}	0	0	b_{21}
δ_{22}	$-b_{22}$	$-b_{22}$	$-b_{22}$
δ_{21}	0	0	$-b_{21}$

3.1.5. Model selection

Since the equilibrium models discussed above are nested within the general model, a test of restrictions can be performed. This test enables us to reject equilibrium models that are not consistent with the data, i.e., enables us to "let the data speak". Since these are structural models, the parameters themselves should be of expected signs. Any estimation that produces unintuitive signs provides indication of model mis-specification and therefore may be rejected. However, even after these tests, one may not be able to reject several models. Eventhough all of these models are nested within the general model, the specific models themselves are non-nested in each other. Hence, non-nested tests are used to choose among the several models that are still not rejected by testing restrictions. More generally, it is possible that the games being tested are not nested in any general model nor in each other. Again, in such cases non-nested model tests have to be performed.

With 3SLS estimates, usually the model that minimizes the sum of squares is considered the "right" model. With FIML as the estimation procedure, Bresnahan (1987) uses Cox tests for non-nested models (which are based on the ratio of the likelihoods of the models) to choose the right model. Gasmi et al. (1992) and Roy et al. (1994) also use likelihood-based non-nested hypotheses tests (Vuong,

1989) for model selection. When using GMM, we may use the equivalents of Cox tests since in many cases, the maximum likelihood estimation has been shown to be a special case of GMM (Hamilton, 1994, p. 14.4).

In discussing model selection among alternative models of competition, we are making the assumption here that the functional form for demand that we use is appropriate. Given that firms' pricing behavior is closely related to the demand functional form, recent studies have focussed on using highly flexible demand models to limit potential for bias (random coefficients logit/LA-AIDS, etc.) or tested among alternative models of demand (Genesove and Mullin, 1998; Sudhir, 2001a).

3.2. The Conjectural Variations approach

The Conjectural Variation (CV) approach, pioneered by Iwata (1974), offers a method by which different types of equilibria can be captured by one parameter. In the CV models, firms are postulated to have conjectures about how competitors will react to changes in their marketing mix and incorporate these conjectures into their decisions. The first-order conditions for firm i in the duopoly case we set up earlier is given by,

$$(p_i - c_i)\left(\frac{\partial q_i}{\partial p_i} + \frac{\partial q_i}{\partial p_j}\frac{\partial p_j}{\partial p_i}\right) + q_i = 0,$$

$$j \neq i, \quad i = 1,2.$$

For the linear model this is

$$(p_i - c_i)\left(b_{ii} + b_{ij}\frac{\partial p_j}{\partial p_i}\right) + q_i = 0, \quad j \neq i, \quad i = 1,2.$$

The term $\partial p_j / \partial p_i$ may be interpreted as a conjecture of firm i about how firm j will change its price in response to a change by firm i. Hence, the term "conjectural variation". The CVs are estimated from the data. As described in Table 2, different equilibria imply different CV estimates for the demand and optimization system discussed above. Note that the CV approach above can be extended to advertising and other instruments as well. As in the menu approach, the two demand equations and the supply equations are estimated using a simultaneous equation instrumental variable estimation approach like 3SLS, FIML or GMM.

Table 2
CV parameters associated with different equilibria for this demand system

Equilibrium	CV parameters
Bertrand	Zero
Leader–follower	Zero for follower, Non-zero for leader
Dominant firm–fringe firm	Zero for dominant with respect to fringe; Negative for fringe with respect to dominant
Cooperative	Positive for both
Competitive	Negative for both

CVs for different competitive instruments, e.g., advertising, and for different demand systems can be different from the values in the table.

Industrial Organization textbooks typically introduce the notion of conjectural variations with a homogenous product market with n firms. In this market, the Bertrand model has a zero CV, collusion has a CV equal to 1 and Cournot competition has a CV of $1/n$. Hence, there is a common notion that the estimated CVs should be below 1, but this is applicable only in the case of a market with homogeneous products. In the case of price competition with differentiated products, there is no unambiguous upper bound. In practice, it is useful to test whether the CV estimates make sense by computing the margins resulting from the estimates. Very high CVs may be meaningless because beyond an upper bound, discontinuities occur and margins become negative. This is meaningless because positive CVs for price imply cooperative behavior and higher margins. For an example of how an upper bound on the CV is derived for a differentiated product model, see Norman (1983).

There are some advantages and disadvantages of the CV approach relative to the menu approach. As the number of players and the number of marketing instruments increase, the number of potential competitive equilibria increases combinatorially. In the menu approach, since a separate estimation is required for each of these equilibria, the estimation and model selection can become potentially cumbersome. The CV approach, on the other hand, nests the different equilibria and therefore avoids the explosion in the number of estimations. Usually, however, when the number of firms and the number of marketing instruments increase, the CV models may not be identified. This means that identifying restrictions need to be made to estimate the model. Sometimes there may not be justifiable reasons for the choice of these restrictions. Nevo (1998) discusses identification issues in CV models.

Some researchers have argued that the estimated conjectures in the CV approach may not be consistent and hence, the CV approach is theoretically unsound. However, recent theoretical work has shown that the conjectural variations approach should be interpreted as a reduced-form way to capture dynamic behavior in a static model. Dockner (1992) derives a conjectural variations equilibrium as the steady state of a subgame perfect (closed loop) Nash equilibrium in a non-cooperative differential game with adjustment costs. This model provides a theoretical foundation for negative conjectural variations. Cabral (1995) formulates a repeated game and shows that the collusive equilibrium is equivalent to a CV equilibrium with a strictly positive conjectural variation. We take the perspective of Lindh (1992) in saying "...conjectural variations should be viewed...as a measure of the deviation from some common standard like the Cournot behavior".

Corts (1999) has investigated conditions under which a CV estimation approach will fail to estimate the right competitive interaction. He finds that in markets with high seasonality (negative correlation in demand states), the potential to mismeasure competitive interaction is severe. In recent empirical work, armed with cost data for the sugar and the spot electricity markets, Genesove and Mullin (1998) and Wolfram (1999), respectively, find that the difference in their CV estimates are not very different from direct measures obtained using cost data. While these studies give us some faith in the empirical validity of the CV approach, more research is needed to reassure us that CV approaches are effective in inferring the right competitive interaction or to highlight conditions under which the technique fails.

3.3. The conduct parameter and the weighted profit approaches

Bresnahan (1989) explains the equivalence of the menu and the CV approach from the point of view of empirical work. In particular, the use of the "conduct parameter" (Porter, 1983), a close cousin of the CV parameter, is proposed. Porter's model is based on quantity competition. To be consistent with our previous discussion, we develop an equivalent model in terms of price competition.

$$(p_i - c_i)\left(\frac{\partial q_i}{\partial p_i} + \frac{\partial q_i}{\partial p_j}\frac{\partial p_j}{\partial p_i}\right) + q_i = 0,$$

$$j \neq i, \quad i = 1,2,$$

is rewritten as:

$$(p_i - c_i)\frac{\partial q_i}{\partial p_i}(1-\theta) + q_i = 0, \quad i = 1,2,$$

where

$$\theta_i = -\left(\frac{\partial q_i/\partial p_j}{\partial q_i/\partial p_i}\right)\frac{\partial p_j}{\partial p_i}$$

or

$$p_i - c_i = -\frac{q_i}{\dfrac{\partial q_i}{\partial p_i}(1-\theta)}, \quad i = 1,2.$$

Therefore, $\theta = 0$ gives the Bertrand–Nash equilibrium. Given that own price-effect is negative, $\theta > 0$ gives a price–cost margin larger than Bertrand–Nash, and therefore, competition is "softer" than Bertrand competition. Similarly, $\theta < 0$ gives a price–cost margin smaller than Bertrand–Nash, and therefore, competition is "fiercer" than Bertrand competition. Therefore, the least structural interpretation of the CV parameter is to interpret it as conduct parameter, which benchmarks competition against Bertrand–Nash competition.

Another continuous parameter approach that avoids the criticisms of the CV approach, but enables us to measure the level of cooperation in a market, is the weighted profits approach advocated by Gasmi et al. (1992). In this approach the model allows an unequal but positive weight on the competitor's profits to allow for a more flexible model than the

Table 3
Summary of steps in implementing NEIO models

Step	Alternatives
Identification of industry	• Industry level analysis with homogeneous product (Porter, 1983) • Few major products/firms (most studies in the literature, e.g., Roy et al., 1994) • Compressing several players into a composite firm (Suslow, 1986, compresses all small firms into a fringe firm; Putsis and Dhar, 1999, combine all national brands into a composite national player, competing against a private label) • More complete sample of products/firms (Sudhir, 2001a)
Choice of data	• Aggregate market level data (most studies) • Individual level data (Horsky and Nelson, 1992; Goldberg, 1995)
Choice of the objective function	• Profits (most studies in literature, e.g., Kadiyali et al., 1996, 2000) • Revenues • Target sales (Roy et al., 1994) • Category profits/ brand profits (Sudhir, 2001b)
Specification of demand functions	• Linear (most studies in literature, e.g., Kadiyali et al., 1996) • Log-linear (Kadiyali et al., 2000) • Log-log functions (Bresnahan, 1987) • LA-AIDS (Putsis and Dhar, 1999) • Logit functions (Besanko et al., 1998; Sudhir, 2001b; Chintagunta et al., 1999) • Logit functions with random (normal distribution) coefficients (Berry et al., 1995; Sudhir, 2001a) • Logit functions with random (finite mixture) coefficients (Berry et al., 1996; Besanko et al., 2000)
Specification of cost functions	• Constant marginal cost (many studies in literature, e.g., Kadiyali et al., 1996) • Linear function of factor costs (Besanko et al., 1998) • Log-linear function of factor costs (Sudhir, 2001a)
Competitive interaction specification	• Menu approach (Roy et al., 1994; Kadiyali et al., 1996) • Conjectural variation approach (many studies, e.g., Vilcassim et al., 1999; Putsis and Dhar, 1999); conduct parameter or weighted profits approach (Sudhir, 2001a) (These techniques have different ways of inferring the type of competitive equilibrium)
Hypotheses on competitive equilibria	• Bertrand • Leader–follower • Dominant firm–fringe firm • Collusive • Competitive
Method of estimation	• 3SLS (many studies) • FIML (Bresnahan, 1987; Gasmi et al., 1992; Roy et al., 1994; Sudhir, 2001b) • GMM (Berry et al., 1995; Sudhir, 2001a)
Model selection methods	• Cox's likelihood ratio tests for non-nested models (Bresnahan, 1987) • Vuong's test (Roy et al., 1994; Sudhir, 2001b) • Minimum sum of squares (many studies)

collusive equilibrium discussed in Section 3.1. This general notion of collusion would allow firms to set prices anywhere on the firms' Pareto frontier (i.e., the set of possible prices that firms might reach if they were able to negotiate, so that they can all achieve higher profits relative to the single period Nash profits).[5] Sudhir (2001a) extends this argument to allow for firms to place negative weights on competitor profits in his analysis of the auto market.

[5] We thank a reviewer for suggesting this interpretation.

The intuition is that firms may price aggressively so as to gain market share in the small car segments to gain the loyalty of first time buyers, so that they can reap the rewards of greater loyalty from these buyers over their lifetimes. However, the same firms will price cooperatively in larger car segments where there is greater loyalty and therefore, aggression does not pay off in additional sales. In general, the negative weights can be used to detect any form of predatory pricing.

For a market with two firms, the objective function for the two firms are assumed to be:

$$\Pi_i = (p_i - c_i)q_i + \phi_i(p_j - c_j)q_j,$$
$$i,j = 1,2, \; i \neq j.$$

Firm i is thus assumed to place a weight ϕ_i on firm j's profits. $\phi_i = \phi_j = 1$ indicates perfect collusion; $\phi_i = \phi_j = 0$ indicates Bertrand competition. When $0 < \phi_i < 1$, $i = 1, 2$, we have intermediate levels of cooperation. When ϕ_i, $\phi_j < 0$, we have highly competitive behavior, relative to Bertrand competition.

The first-order conditions for this model are

$$\frac{\partial \Pi}{\partial p_i} = (p_i - c_i)b_{ii} + \phi_i(p_j - c_j)b_{ij} + q_i = 0,$$
$$j \neq i, \quad i = 1,2.$$

3.4. NEIO modeling and estimation: A summary of steps

The preceding example provided a quick review of the basic methodology. We now summarize the various steps and the alternative approaches that researchers have used in building and estimating NEIO models in Table 3. These steps begin with an identification of an industry context, specification of objectives of players, specification of demand and cost functions, specification of competitive interaction among players (game employed), choice of relevant data, estimation and testing models and hypotheses. The specific choice would depend on the problem of interest and the industry/context that is being studied.

4. Applications of NEIO framework to issues of interest to marketers

As the example above shows, the essence of an NEIO model is modeling demand and first-order optimization conditions of firms, and the econometric estimation of the same. In this section, we elaborate on some issues in applying the above framework to marketing problems. We will discuss issues in the following three dimensions: modeling demand-side issues of interest to marketers, modeling cost, and modeling issues in competitive behavior. We next summarize the pattern of, and reasons for, the evolution of the literature. We end with a discussion about possible directions for future research in this area.

4.1. Modeling richer demand structures

4.1.1. Other functional forms of demand

In empirical applications, it is important to ensure that the demand function used describes accurately the industry and firm being studied. Recall that the functional form of demand has implications for optimal profit margins and thus, the supply equations. In a simple linear demand model, the own and cross price effects are constant at all levels of prices; in a log–log model, the own and cross price elasticities are constant at all levels of prices. While these functional forms are useful in estimating pure demand models, greater flexibility in the demand models are needed when also estimating the supply-side models. Marketing researchers have been using more flexible demand models in their research of late: Putsis and Dhar (1999) use an LA-AIDS demand model, Besanko et al. (1998), Sudhir (2001b) and Chintagunta et al. (1999) use a logit model and Sudhir (2001a) uses a random parameters logit model. Researchers also test the appropriateness of functional form used for their markets; for example, see Genesove and Mullin (1998).

In recent theoretical work on marketing channels, Lee and Staelin (1997) and Tyagi (1999) have shown that the functional form crucially determines a retailer's strategic behavior (retail passthrough). Demand models characterized by Vertical Strategic Substitutability (VSS hereafter; e.g., linear, homogeneous logit models) always have retail passthrough of less than 100%, while models characterized by vertical strategic complementarity (VSC hereafter; e.g., multiplicative model) have passthrough greater than 100%. Sudhir (2001b) explicitly tests whether the VSS or VSC implications best fit the data by using both a homogeneous logit (VSS) or the multiplicative model (VSC). He finds the VSS implications of the logit are more consistent with the data. Flexible models such as heterogeneous logit and LA-AIDS allow passthrough to be greater than or below 100% and should be potentially useful in future research modeling channel behavior.

The use of discrete choice models has vastly increased the usability of the NEIO approach to problems of relevance to marketers. Most studies in the NEIO approach have focussed on multiple firms selling fairly homogeneous products or a limited number of differentiated products. In some cases, a small number of products truly reflect the competition in the market (for example, rivalry between Coke and Pepsi modeled by Gasmi et al., 1992; rivalry between Kodak and Fuji in the film market by Kadiyali, 1996). In other cases, the number of competing products is restricted to a few major players to enable ease of estimation. However, most markets of interest to marketers have multiple players, and multiple products, and also horizontal and vertical differentiation. The simple linear model is incapable of handling such markets for the following reason.

In the example of Section 3 above, there are two firms, each manufacturing one product, leading to four price effects to be estimated in the demand function. When the number of products increases as in the auto market or breakfast cereal market (or the number of firms), the number of parameters to be estimated explodes. For example, in a market with 30 products there will be 900 price effects in a linear demand model.[6] A solution to this problem is to impose greater structure on the demand specification, so that fewer parameters need to be estimated. A Lancasterian approach (Lancaster, 1971), where utility is based on the product characteristics, can serve to impose a suitable structure on demand. The demand equations are derived by aggregating individual choices in a utility maximizing framework. Both the deterministic and random utility approaches have been used.

An example of a deterministic utility approach is that of Bresnahan (1987). He assumes that all product characteristics can be summarized to a single number called product quality by an appropriate function of product characteristics. Consumer valuations of quality are assumed to be uniformly distributed. Feenstra and Levinsohn (1995) allow product characteristics and consumer preferences for these characteristics to be multidimensional. With these assumptions, the demand equations for the products are constructed. Products with similar characteristics will compete against each other than products with divergent characteristics under these specifications.

In many situations, several unobserved characteristics affect consumer choice. Accordingly, the random utility framework has been adopted in recent work. In this framework, there are two components of utility: a certain deterministic component observed by the researcher, and a random component unobserved by the researcher. Assumptions about the random component of the utility are made explicit, taking into account the market characteristics. When the random component of utility is assumed to be independently and identically extreme value distributed across products, we get the logit model. By assuming appropriate correlations across products for the random component, we can generate the nested logit model.

Berry (1994) develops a general contraction mapping approach to compute the mean level of utility for a product across consumers for a general class of models that include the logit, the nested logit and random parameters logit models, using observed market shares. This mean utility can then be used as a dependent variable for the demand equation in estimating the parameters for the utility associated with the characteristics of the product. Verboven (1996) estimates a nested logit model in analyzing inter-country price discrimination by firms in the European car market. Berry et al. (1995, henceforth BLP) implement this method in a random parameters logit model of the US auto market, where the coefficients of utility for characteristics are assumed to be normally distributed. In their paper, they assume that the firms are involved in Bertrand competition. Sudhir (2001a) generalizes the BLP analysis by allowing for deviations from Bertrand competition in different segments of the US auto market. He finds that firms

[6] This problem occurs even if we use a log-linear or log-log model.

are more competitive in the smaller car segments and more cooperative in the larger car segments.

4.1.2. Aggregate versus individual-level data

In addition to the product differentiation issue discussed above, another important issue in demand specification is that of the level at which demand is specified. Marketing researchers have debated the use of individual choice data versus market-level choice data. Most studies in the NEIO tradition in marketing have used aggregate firm-level data on sales and prices to specify both the demand and the marketing mix optimization rules. Marketing research in the consumer choice area has used both aggregate and individual level, and in particular, the advances made in estimating various dimensions of choices using individual-level data are very impressive. Using mainly aggregate data in the NEIO tradition means that the degree of sophistication in demand modeling is much less than the one in the consumer choice literature using individual-level data.

There are some notable exceptions, however, in the NEIO literature, which use individual-level data. Horsky and Nelson (1992) and Goldberg (1995) estimate models of the automobile market using survey data from individuals. This enables them to model demand heterogeneity at a great level of detail. Horsky and Nelson use their model to do optimal product positioning given the estimated demand and cost characteristics under the assumption of Bertrand competition among the auto manufacturers. Goldberg attempts to infer whether the voluntary export restraint imposed by Japanese auto manufacturers had any impact on the auto market in the US during the 1980, assuming that firms were in Bertrand competition with each other.

When dealing with individual data, researchers use a two-stage estimation procedure. In the first stage, they estimate the demand parameters using standard choice modeling techniques. In the second stage, they aggregate market shares from individual choice data and then estimate supply-side parameters (costs and competitive interactions), subject to the demand estimates from the first stage. The gap that remains in using individual-level data in NEIO studies is that, techniques to estimate general models of competition have not yet been developed. Both Horsky and Nelson and Goldberg assumed the Bertrand–Nash equilibrium, rather than infer the competitive interactions from the data.

4.2. Modeling richer cost structure

There has been much less sophistication in cost-side specification relative to the demand-side developments discussed above. Typically, constant marginal cost specification has been used (see Jarmin, 1994, who allows costs to fall over time due to learning, for an exception). While many studies have estimated costs as a single parameter, Besanko et al. (1998) estimate a linear function of production cost factors while Sudhir (2001a) estimates a log-linear function of production cost factors.

Functional forms of demand and cost need to be carefully considered in studies that use conduct parameter estimation procedure. Bresnahan (1989) discusses the issue of identification of the conduct parameter under a variety of functional forms for demand and cost. A major conclusion is that a minimum amount of nonlinearity is needed to identify conduct parameters. For example, Parker and Roller (1997) use a semi-log form of demand to enable identification of this parameter. Researchers are advised to verify that the conduct parameter is indeed identified in their models by using appropriate functional forms of demand and cost.

4.3. Richer specification of competition

4.3.1. Alternative objectives

The model in Section 3 assumes that firms maximize profits. This is the NEIO counterpart of consumer choice model assumption that consumers maximize utility. Researchers have speculated that firms often maintain market share and may have other goals as well. Roy et al. (1994) assume that the objective of firms is to be close to a preset target, where the targets are treated as exogenous to the analysis. Sudhir (2001b) allows for alternative objectives (category profit maximization, brand profit maximization, charging a constant markup) and finds that the best fitting model is one where the retailer maximizes category profits. Other possible objectives include maximizing profits subject to market share, or subject to a certain level of consumer surplus (to avoid antitrust activities), or minimizing time to market. One difficulty to keep in mind is that closed-form, unique and econometrically identifiable optimization rules cannot be found for all games for these alternative objectives.

A related issue is that most NEIO studies have assumed that firms choose prices, (or advertising or capacity) to maximize profits. The theoretical game theory literature has shown us that changing the competitive game from price to quantity competition significantly alters results. Therefore, an important question is whether the assumption of price competition rather than quantity competition is correct. Raju and Roy (1999) find that for the US microprocesser industry, price competition fits the data better than quantity competition. They argue that a reasonable case can be made that quantity competition is likely in this industry, and therefore, finding that price competition better describes the data is reassuring, given that many marketing studies use price competition. It must however be remembered that the notion of quantity competition is widely used when modeling homogeneous or monopoly markets, because industry quantities essentially determine industry prices. In contrast, in differentiated product markets, with excess capacity (most marketing studies fall in this category), price competition is theoretically more appealing and is therefore widely used in theoretical studies.

4.3.2. Continuous versus discrete choices of marketing mix

In the example discussed in Section 3, the price decision of firms is a continuous choice variable. However, in many classes of games, strategic decisions may be only qualitative, e.g., entry and exit games are 0–1 variables. Modeling of the retailer's decision to sell a product offered by a manufacturer is similar. In these kinds of situations, we need to make inferences about player's incentives from qualitative data.

Bresnahan and Reiss (1991) extend the approach of single person discrete choice models (McFadden, 1982; Hausman and Wise, 1978) that has been widely used in marketing to analyze consumer choice to the multi-person discrete choice framework. In singe person choice models, parameters of consumer preferences are estimated using threshold models of consumer behavior. In multi-person choice models parameters of agents' (firms') payoffs are estimated using threshold models of games.

As an illustration of the methodology, consider the example of an entry game used by Bresnahan and Reiss involving two firms. Each firm has two actions: to enter or not to enter. Let us denote the action of player i as a_i where $a_i = 0$ indicates that firm i does not enter and $a_i = 1$ indicates that firm i enters. The following tables represent the two firms' payoff matrices. Π^i_{jk} indicates the payoff to firm i where firm 1 takes actions j and firm 2 takes action k. Δ^i_0 indicates the increase in profits to firm i when firm i enters a market with zero competitors. Δ^i_1 indicates the decrease in profits to firm i when firm j enters a market in which it had a monopoly. By economic theory, we expect $\Delta^i_1 \leqslant 0$.

Player 1's payoffs

	$a_2 = 0$	$a_2 = 1$
$a_1 = 0$	Π^1_{00}	Π^1_{01}
$a_1 = 1$	$\Pi^1_{00} + \Delta^1_0$	$\Pi^1_{01} + \Delta^1_0 + \Delta^1_1$

Player 2's payoffs

	$a_2 = 1$	$a_2 = 1$
$a_1 = 0$	Π^2_{00}	Π^2_{01}
$a_1 = 1$	$\Pi^2_{00} + \Delta^2_0$	$\Pi^2_{01} + \Delta^2_0 + \Delta^2_1$

In a Nash equilibrium,

$$a^1 = 0 \Leftrightarrow \Delta^1_0 + a^2\,\Delta^1_1 \leqslant 0,$$

$$a^2 = 0 \Leftrightarrow \Delta^2_0 + a^1\,\Delta^2_1 \leqslant 0.$$

For an econometric model, we need a stochastic specification for unobserved profits. For their purpose, Bresnahan and Reiss treat the Δ^i_1 as constants and the Δ^i_0 as random variables that vary across firms and markets. Assuming that Δ^i_0, the incremental profit firm i receives as a monopolist in any given game, is a linear function of observables (X) and unobservables (ε), i.e., $\Delta^i_0 = X\beta_i^{\,0} - \varepsilon^{\,i}$, then the structural equations determining the Nash equilibria of this game are

$$y^*_1 = X_1\,\beta^1_0 + a^2\,\Delta^1_1 - \varepsilon^1,$$

$$y^*_2 = X_2\,\beta^2_0 + a^1\,\Delta^2_1 - \varepsilon^2,$$

where

$$a^i = \begin{cases} 0 & \text{if } y_i^* < 0 \\ 1 & \text{if } y_i^* < 0 \end{cases} \qquad \text{for } i = 1, 2.$$

These two equations form a discrete dummy variable endogenous system for the unobserved y_i^*. This system is a special case of the systems considered by Heckman (1978). From here, the joint probability distribution of Δ_1^i, $i = 1, 2$, can be estimated and the thresholds of entry recovered. Their model is used to explain the number of entrants in the market, and the threshold of market size that is needed to sustain these entrants. They also illustrate how to develop models for sequential (leader–follower) models and collusive games.

Summarizing, the NEIO framework can be extended to estimate discrete choice marketing strategy variables, but the general conduct parameter estimation approach is yet to be implemented.

4.3.3. The dynamics of competition

The model discussed in Section 3 is a one-period or static model of competition. The reaction function literature allows for dynamic competitive effects, but is not structural in nature. Modeling dynamics in a fully structural context turns out to be a challenging task. We discuss three approaches used in the literature. Fully structural dynamic models of competition have not yet been estimated in the NEIO literature; in Section 5.3, we discuss the shortfalls of current developments in the area.

An attempt at modeling dynamics is done by Roberts and Samuelson (1988). They develop a model of advertising as a goodwill stock (see also Vilcassim et al., 1999). All competitive effects of advertising greater than two periods are summarized by a constant in this model as these effects cannot be separately identified econometrically. In other words, only two-period dynamic effects are estimable in this model.

Another attempt at modeling dynamics is made by Slade (1995). Her model allows inter-temporal dynamics in price and advertising to last several periods and chooses the appropriate lags based on the data. That is, unlike Roberts and Samuelson (1988) where effects greater than two periods cannot be estimated, she allows the data to determine how many lags should be included (see also Chintagunta et al., 1999, for a similar approach). Slade finds that for the saltine cracker market, the appropriate number of lags to consider was two. She uses a Kalman filter approach to estimate the model. Interestingly, she finds that what may be usually considered as a collusive equilibrium in a static context is an outcome of a non-cooperative game when inter-temporal dynamics are considered. This shows that modeling dynamics can give us greater insights into the behavioral rationale underlying the observed equilibrium. One should add that the descriptive value of the static analysis, however, continues to be relevant.

A third approach by Slade (1992) is to focus on off-equilibrium behavior. She estimates a dynamic model of demand and supply of the Vancouver gasoline market during a price war. While this paper is close in spirit to the reaction function estimation discussed earlier, it differs from that stream of research in that, reactions are explicitly linked to demand and cost characteristics in the market. Thus, this paper provides a more structural approach to reaction functions. She classifies the firms in the market into two types: majors representing major oil companies and independents. She attempts to understand the out of equilibrium strategies used by firms during price wars, by estimating the reaction functions using a Kalman filter. She allows for asymmetric reactions to price increases/decreases and also allows for nonlinearity of reactions (by allowing reactions to depend on price levels), a feature similar to reaction function studies. She finds that reaction parameters are not constant over time. However, the stochastic process that generates the variation is stationary, indicating that there are long run stable values for these parameters.

4.3.4. The issues of endogeneity, simultaneity and periodicity

As discussed in Section 1, the question of endogeneity and simultaneity need to be addressed in applying the model of Section 3 to marketing contexts, as well as in extending the model to other marketing strategy instruments. If the model of Section 3 were a model of competition between two retailers, are the prices truly endogenous to retailers or are they determined by manufacturers? Since demand for the product is also a function of national manufacturer advertising, should we treat pricing decisions as endogenous to the retailer but treat the advertising as exogenous? NEIO studies have typically examined manufacturer pricing and advertising decisions, and these decisions are both endogenous to manufacturers. The issue of simultaneity of decision-making is also relevant here. For example, if capacity decisions or product line decisions or entry decisions are made prior to the decision on pricing and advertising, then these decisions can be treated as exogenous.

NEIO studies in marketing have dealt with the issues at various levels. In many papers in marketing that use scanner panel data (for example, Kadiyali et al., 1996), features in newspapers are treated as exogenous decisions to manufacturers. In Besanko et al. (1998), Kadiyali et al. (2000) and Sudhir (2001b), both manufacturer and retail price are modeled as endogenous, with optimization rules for both. Kadiyali et al. (2000) treat features and displays as endogenous, but no optimization rules for these are specified. Sudhir (2001b), however, could not reject exogeneity of features and therefore treats it as an exogenous variable. Researchers are therefore advised to perform econometric tests to determine whether or not to treat variables as endogenous, and then determine if the endogeneity needs to be modeled as a separate process or whether it is enough to use instruments to account for endogeneity.

An econometric issue here is the choice of appropriate instruments for variables that are assumed to be endogenous. Typically, demand and cost shifters have been used. In certain situations, lagged values of endogenous variables may be appropriate. BLP (1995) and Sudhir (2001a) use averages of own firm's other products and other firm's products as instruments by making a supply-side argument in analyzing the auto market. In an analysis of multiple markets for breakfast cereals, Nevo (2001a) uses prices in other markets as instruments for prices.

The issue of periodicity of decision-making is trickier. For example, in modeling manufacturer competition using scanner data, do we believe that manufacturers set price weekly? An econometric test of endogeneity may be needed to determine whether these variables are indeed exogenous to weekly scanner data. A variation of the Hausman test to test endogeneity was introduced by Besanko et al. (1998) and has been applied by Kadiyali et al. (2000) and Sudhir (2001b). A potentially difficult situation would be if different decisions have different periodicity, e.g., pricing decisions made weekly, but advertising decisions made monthly. That is, pricing decisions are endogenous in weekly data, but advertising is endogenous only once in four weeks. Therefore, periodicity of decision making and time aggregation/disaggregation are important issues to bear in mind in implementing NEIO models.

4.3.5. Incomplete information

The model in Section 3 above assumes that firms have full information about demand functions as well as each other's cost functions. In many competitive situations, however, there may be incomplete information about demand and cost conditions. Modeling this in a fully structural framework is limited by the lack of detailed data on firm decisions. Hence, reduced-form hypothesis testing approaches are more widely used for such testing. Game theory papers on agency or principal-agent problems describe the effects of lack of information on equilibrium outcomes, and these effects can be tested with data. For example, Shepard (1993) tests the role of monitoring issues on which gas stations are franchised out and which ones are company owned. She finds that full-serve stations are more likely to be franchised out because of the difficulty in monitoring a manager's effort in providing this service.

However, as discussed earlier, hypothesis testing does not provide structural estimates of demand and cost which are policy invariant. The task of building and estimating a structural model is significantly harder under incomplete information. Miravate (1997) estimates consumer preferences for local telephone calling deals, given private information between consumers and local telecommunication companies. In a market, consumers are faced with a nonlinear price schedule that consists of a fixed fee and a marginal rate that are both functions of the minutes called. He assumes that consumer types (in terms of their calling preferences) in the population may be known by their demographic characteristics with any asymmetry of information being captured by a beta distribution. Based on this assumption, he derives the optimal demand for the various types and the optimal fixed fee and marginal rates for each type. He then computes the expected total payments for consumers and finds that total expected tariffs are a linear function of demographic characteristics when all information about consumer types is captured by the demographic characteristics. However, if the asymmetry of information is relevant, i.e., the beta distribution is not degenerate, then the expected tariffs include interaction terms of demographic characteristics. By testing the significance of the interaction terms he concludes that there exists significant asymmetry of information. He also finds that failure to account for the asymmetry of information in his model leads to systematic overestimation of demand.

Therefore, accounting for the effects of incomplete information, not just between consumers and firms, but also between firms, is critical to estimating correct demand, cost, and competitive conduct parameters.

4.3.6. Modeling intra-channel strategic behavior

Manufacturers in many product categories sell their products through a retailer to the consumer. A model of market response for a manufacturer therefore needs to take into account not only how consumers and competing manufacturers react to the marketing mix, but also how the members of the channel react to the marketing mix. Measuring channel response, simultaneously with consumer and competitive response, is therefore managerially important.

With scanner data, in general, the wholesale prices are unobserved. Researchers have in the absence of wholesale price information made the assumption that retailers charge a constant margin. With this assumption, wholesale prices can be known up to a constant margin and they then infer competitive behavior among manufacturers. Prior studies have usually found cooperative behavior among manufacturers with this assumption. Given that retail prices are used for the analysis, it raises the question whether we may be misinterpreting retailer category management as manufacturer cooperation. To test this issue when wholesale price data is unavailable, Sudhir (2001b) uses a game theoretic modeling approach to infer wholesale prices. He tests for alternative models of manufacturer–retailer interaction such as manufacturer Stackelberg Leader–Follower behavior and Vertical Nash behavior. Cotterill and Putsis (2001) also tests for alternative models of manufacturer–retailer interaction in the absence of wholesale price data. Alternatively, Kadiyali et al. (2000) use actual wholesale price data to tackle the issue of incorporating channel response and infer the balance of power between manufacturers and retailers (see also Parker and Kim, 1999).

5. The evolution of literature: Retrospective and prospective

We now discuss how the literature has evolved and how we expect it to evolve in the future. As in the previous section, we organize this discussion into those relating to demand, cost and competition issues. Clearly, theoretical developments in game theory, and marketers' empirical observations from SCP studies have given us enough puzzles to empirically explore further. We argue that the evolution of this literature has been mainly data- and methodology-driven, and these two constraints will also shape the future direction of this literature.

5.1. Demand: looking back, looking ahead

The most active area of development has been in sophisticated demand modeling using widely available aggregate data. Advances in the economics literature (e.g., BLP) have fueled these developments. Its quick diffusion in marketing is not surprising given the rich tradition of demand modeling in marketing. In fact, this is an area where more bridges between marketing and economics literature can be built. There are several directions this literature can profitably pursue. BLP (1995) illustrated how we can model heterogeneity among consumers using the distribution of consumer demographics (income) that are usually available with consumer data. This technique of using aggregate distribution information to effectively account for consumer heterogeneity is further enhanced in the work of Nevo (2001b) and Petrin (1999). These methods to infer demand parameters with purely aggregate data should be of great interest to marketers, because in practice managers usually have much greater access to aggregate store-level or market-level data rather than individual level data.

Secondly, as mentioned previously, marketers have advanced techniques for estimation of demand using individual data as well as analyzing the biases in using aggregate versus individual-level demand (Gupta et al., 1996). This would be a promising area for future work, because with individual level data, dynamics in consumer preferences can be better captured (Erdem, 1996). Studying the role of consumer dynamics on firm pricing dynamics is a difficult but important issue. Bayesian estimation tools for modeling demand offers great promise in estimating finer levels of heterogeneity across firm demand, cost and competition parameters in the NEIO framework. In the short- to medium-term, we therefore expect the literature to focus on further sophistication in modeling heterogeneity in the aggregate demand-discrete choice arena and the use of Bayesian methods to capture the heterogeneity on both the demand and the firm side.

5.2. Cost and supply: looking back, looking ahead

On the cost dimension, specifications used in marketing have been relatively simple. An important reason for this is that given weekly scanner data used in several marketing studies, it is not always possible to find weekly cost-side instruments. Second, NEIO studies in economics have been more varied in their application across industries, whereas marketing studies have been mainly confined to packaged good industries. Given issues of retailer versus manufacturer margins when using local market data, the lack of data on various manufacturer–retailer transfer payments (for e.g., slotting allowances) and the difficulty of estimating hedonics or characteristic-based costs for these industries, a richer cost specification is not easy. That said, the hope is that marketing studies in the future will explore non-packaged goods industries and get past some of the cost specification issues associated with these.

Another area of importance is the modeling of institutional details of supply in a particular market. An example of detailed supply-side modeling in economics is the previously cited Suslow's model, where first-time and recycled aluminum are treated differently in modeling and estimation. Berry et al. (1996) model in great detail the hub and spoke structure of the airline industry. Researchers in marketing have paid great attention to institutional details in modeling channel behavior (see Section 4.3.5). Marketers are now making strides in this area as theoretical and data constraints are relaxed. As we discussed in Section 4.3.5, a unique innovation of marketing to the NEIO literature has been the study of manufacturer–retailer relations. These studies have been mainly confined to the study of pricing. It would be instructive to expand the scope of this research to other channel decisions like advertising or promotions. Additionally, models of multiple retailers interacting with multiple manufacturers in a complete intra- and inter-channel model of competition are yet to be estimated. Relevant data for this type of analysis may be hard to get. While the relationship between manufacturers and retailers has been explored in some detail because of data availability, the relationships between a firm and other intermediaries (including suppliers rather than retailers) remains an area yet to explored in the marketing NEIO literature, mainly because of data constraints. Non-packaged goods industries (e.g., high-tech products with complex supply chain partnerships, or pharmaceuticals with R&D processes) are especially well-suited to expand the literature in this area.

5.3. Competition: looking back, looking ahead

On the competition dimension, several marketing studies have explored a variety of issues in pricing competition. Pricing is clearly a very important marketing mix element, and therefore, it is not surprising that it has been the focus of the majority of attention as the literature has evolved. Examples include Roy et al.'s (1994) study of price competition between Ford and Chrysler, Kadiyali et al.'s (1996) study of product line pricing decisions of two firms, Sudhir's (2001a) study of price competition across (car market) segments, Vilcassim et al.'s (1999) study of hierarchy in with three firms in the market, Putsis and Dhar's (1998) study of national brand-private label price competition. There have also been at least two studies of manufacturer–retailer pricing competition (Sudhir, 2001b; Kadiyali et al., 2000).

All these studies have found that simple Bertrand–Nash pricing is not a good assumption to make, and firms in markets have varying degrees of market power because of the efficacy of brand positioning (measured by own- and cross-price elasticities), and their low costs. All these applications have typically been driven by researchers' interest in pricing policies under different marketing strategy situations. We expect the future direction of this literature to be comprised of other applications of the NEIO framework to other marketing strategy situations. In particular, we expect a more complete analysis of manufacturer–retailer pricing interactions and the effect of new channels of distribution on these relationships in the immediate future. Data availability is likely to be the crucial limiting factor.

An issue with discrete choice demand model NEIO papers using aggregate data (e.g., BLP) is that they impose the assumption of Bertrand pricing among firms. (As we mentioned in Section 4.1, this is also true for models that use discrete choice models using individual-level data). For these functions, there is no solution yet to estimate separate competitive interactions among several firms. Sudhir (2001a) has overcome this issue by estimating segment-level competitive interaction parameters among firms, effectively reducing the number of parameters that need to be estimated. However, future work will need to decompose the competitive interactions between products in terms of simpler basic primitives to estimate a full-blown model of competitive interactions among all products (whether the application is to pricing competition, or other types of competition).

Applications of the NEIO framework to advertising competition have been more limited (e.g., Vilcassim et al., 1999) and therefore, several issues remain to be explored. This is possibly because it is harder to obtain advertising GRP data for markets, especially at the weekly or other high frequency level at which pricing data are available. Also, advertising competition is likely to be more dynamic than pricing competition given its long-lived demand effects. This poses a significant challenge to researchers, and further developments in the dynamics of competition will enable researchers to study these issues in greater detail.

An example of a future application in the advertising competition arena is promotion scheduling. Theoretical research has identified demand and advertising cost conditions for when it makes sense to pulse advertising or to have to steady stream of advertising. Roberts and Samuelson's (1988) study of advertising accounting for dynamic advertising effects and advertising costs provides a building block for an empirical analysis of these issues. It would be instructive to generalize their demand, cost, as well as goodwill specifications, to test optimal market and competitive conduct scenarios for alternative advertising schedules.

Competitive analysis of promotions like features, displays, etc., has not yet received attention in the marketing literature. This could be because it is not easy to formulate the variable cost structures of these marketing mix variables. Additionally, the techniques of estimating discrete choice models described above in Section 4.3 could be used to study feature and display competition, but to combine them with continuous choice of pricing is a challenging task. Future applications of these techniques especially to retailer competition can be very instructive. This could also answer the long-standing debate about whether there are mixed-strategy equilibria in promotions (although we await the finessing of dynamic equilibria testing to better test this).

Another marketing mix variable that has been less studied is choice of location. The limited attention to this area is possibly again because of data constraints, as well as the discrete nature of this choice variable. Data of firms in an area, with location coordinates, as well as other dimensions of competition like price, quantity, etc., are needed to estimate such models. An example of such work is Davis (1997), who analyzes spatial competition among movie theaters. However, the insights offered by modeling competition in an NEIO framework are yet to be explored fully.

A marketing mix/product design variable that has received some attention in the marketing literature is network externalities. Shankar and Bayus (1999) analyze the impact of network externalities on competition in the home video game player industry. This literature points the way for studying switching costs in general in the context of either product life-cycle or entry. Given the widespread importance of network externalities in the emerging area of e-commerce, insights on this topic should be of great value to managers.

A general issue with measuring marketing mix competition is to test if competition varies over time.

There are two ways to do this. The first is to develop fully structural dynamic models of competition, and the second is to estimate a static model of competition with a time-varying conduct parameter. The techniques for fully structural dynamic models of competition have not yet been developed in the NEIO literature. Pakes and McGuire (1994) have developed techniques using Markov-perfect Nash equilibrium concepts to model the dynamics of competition (where last period's firm choices are sufficient statistics for predicting future behavior). The estimation is based on a computationally intensive dynamic programming technique. However, there are two roadblocks in widespread application of these methods to NEIO framework. The first is that the Markov-perfect Nash equilibrium assumption needs to be relaxed because it is restrictive, and second, the estimation needs to be extended to forms on competition other than the currently possibly set (i.e., Bertrand, fully collusive, etc.).

A second solution to estimating whether competition varies over time is to measure time-varying conduct parameters. This has so far not been attempted in marketing. An example in economics is Parker and Roller (1997), who, in a study of competition in the cellular phone market, estimate the conduct parameter as a function of multimarket contact and cross-ownership. As the multimarket contact and cross-ownership changes over time, they analyze the impact of competitive behavior. For future applications in marketing, one simple alternative is to specify the conduct parameter as a hazard function or as a logistic function and to examine whether there are any cycles of marketing mix competition. The current NEIO solution is Porter's (1983) endogenous switching regression model of (pricing) conduct parameters that alternate between periods of collusion and breakdown of collusion. A general specification of the time-varying conduct parameter is needed to provide more insights into the dynamics of competition. This is a simpler solution to capturing the dynamics of competition than awaiting more realistic models of Markov-perfect competition.

A direct and especially interesting future application of time-varying competition is the study of marketing mix efficacy in different stages of the product life cycle. In the NEIO literature, Greenstein and Wade (1998) have addressed this issue. They analyze how competitive conduct changes over the product life cycle in the mainframe computer market. The constraint to expanding this study to marketing might be the data requirements (we would need price, sales and other marketing strategy instruments by brand from the start of the market to its maturation). Another future application might be the study of early and late mover advantages, which can also be addressed by estimating time-varying demand, cost and competition parameters.

Another application of time-varying competition is in the area of new product introduction. Two papers in marketing have addressed some aspects of this. Kadiyali et al. (1996) analyze how a new product introduction changes competition in the marketplace. Shankar (1997) analyzes what the best entry strategies are when accounting for competition. However, many aspects remain to be explored in much greater detail. For example, how the market moves from the competitive disequilibrium caused by market entry to a new competitive equilibrium is of interest to marketers, and can be examined by using a time-varying conduct parameter. Additionally, models of how firms learn of each other's cost structures or of consumer demand for a new product and the resulting competitive structure remain to be estimated.

In contrast to pricing and advertising, many marketing decisions are discrete and dynamic in nature. The dynamics of these are also slowly being developed. Ericson and Pakes (1995) develop estimation techniques for dynamic models for R&D investment and entry-exit decision of firms using the Markov-perfect equilibrium concept discussed above. While R&D investment decisions are continuous, entry-exit decisions are discrete. They use their model to analyze the entry and exit of differentiated products in a market. This approach is used to test alternative theories of firm dynamics and the evolution of markets in Pakes and Ericson (1998). However, the same issues discussed earlier, i.e., modeling dynamics more generally than Markov-perfect behavior and more general models of competition in the conduct parameter framework, need to be developed before these methods can be applied to gain insights.

In the age of the Internet, firms can very easily track pricing behavior of their competitors and react virtually instantaneously by appropriately changing their prices. Markov-perfect equilibrium models are therefore appropriate to model price competition on the Internet. We therefore believe these types of models can be useful to model the ease with which competitors can react in many Internet markets.

A final frontier in analyzing more realistic models in competition is accounting for incomplete information in structural models, as we discussed in Section 4.3.4. Apart from the methodological difficulties, a major bottleneck in estimating structural models of incomplete information is that it is very difficult to obtain detailed data on decisions at a very disaggregate level. Fortunately, in the area of auctions, there is detailed data on the bidding process across multiple auctions. Here is where the most progress on estimating structural models of asymmetric information has been made (Porter, 1995). With the easy availability of auction bid data on internet sites such as eBay , this could potentially be a very promising area for research; for e.g., see Bajari and Hortacsu (2000). Given the importance of consumer-to-consumer auctions in the internet age, this should be of substantive interest to researchers in marketing. Another potentially attractive area would be the analysis of sales force compensation. Sales force compensation models are principal-agent models in an asymmetric information framework. Since detailed data on sales force performance under different compensation schemes should be available in many firms, one can estimate a structural model of asymmetric information to infer distributions of sales force risk preferences and utilities. In the absence of such detailed data, researcher could collect experimental data to refine estimation techniques for this class of problems. In short, we believe there are a number of opportunities waiting to be explored in this area.

6. Conclusion

Structural models in the NEIO framework provide estimates of, and insights about, the underlying competitive game, demand and cost structures for a specific industry. We have argued in this paper that they are therefore extremely useful for managerial decision-making, and specifically, for marketing mix decisions. As we stated in the introduction, there are several benefits to estimating NEIO structural models.

A major benefit of structural NEIO estimation is that it enables theory testing. Game theory offers competing theories under different assumptions leading to different predictions. For example, Green and Porter (1984) suggest a theory of dynamic competitive behavior that suggests procyclical behavior, i.e., prices rise during periods of high demand of a market and fall during periods of low demand for a market. Rotemberg and Saloner (1986) in contrast develop a theory that predicts countercyclical behavior. Ratomberg and Saloner use estimates of competitive behavior from Porter (1983) to show that the railroad cartels of the 1880s behaved in a manner consistent with procyclical pricing implications. Bresnahan (1987) shows that the auto market behaves consistently with the procyclical prediction of Rotemberg and Saloner. NEIO research can thus serve to judge the appropriateness of theories.

An issue with such theory testing is that while the tests are based on structurally rich and industry-specific studies, it is not clear whether and how these findings can be generalized. We have argued previously that managers care both about strategic generalizations across industries and strategic specifics of their industry. There are several studies that combine the methodology of NEIO and yet study several closely related markets. For example, Parker and Roller (1997) and Nevo (2001a) analyze firm behavior in the cellular telephone and breakfast cereal markets, respectively, across multiple geographical markets within the United States. Verboven (1996) analyzes price discrimination behavior in different countries of the European car market. Sudhir (2001a) analyzes multiple segments of the US auto market to infer differences in competitive behavior across different segments. The studies across closely related markets analyze how similar firms adapt their behavior in different markets to account for the variations in structural characteristics of these markets.

Putsis and Dhar (1999) use a hybrid of NEIO and SCP approaches. They infer competitive behavior for about 42 different frequently purchased product categories across 59 local markets using NEIO techniques that account for the endogeneity and simultaneity of firm choices. In a second step (in the SCP tradition), they meta-analyze their estimates of competitive behavior against structural characteristics of the different product markets to draw conclusions about the relationship between competition and structural characteristics of a market. The criticism about the appropriateness of pooling competition estimates across disparate markets is somewhat tempered by the fact that all of these product categories are frequently purchased consumer goods.

To obtain generalizable results, researchers need a number of such industry specific studies in similar competitive contexts. At this stage, the volume of empirical research in this area is still too limited to perform a meaningful meta-analysis; hence, the lament of researchers in industrial organization and competitive strategy researchers in the areas of business strategy and marketing about the paucity of empirical studies in this area. In a survey of applications of game theory to competitive marketing strategy, Moorthy (1993) says "...the ratio of theoretical to empirical work is...unpleasantly large". Ghemawat (1997) argues that the inability of game theory-based new industrial organization to influence business strategy is primarily due to the lack of empirical work. We look forward to more studies that would enable robust generalizations.

In addition to theory testing, the structural estimates of NEIO models are managerially useful. First, the estimates have behavioral meaning and hence, managers can easily interpret them. Second, since the estimates are policy invariant, they can be used to perform "what-if" analyses. That is, by estimating detailed structural parameters of demand, cost and competitive interactions, a manager can evaluate the impact of decisions such as the effect of a introducing a new product or line extension, merger with a competitor, impact of a price change, etc. In one of the early papers in marketing in the NEIO tradition, Horsky and Nelson (1992) obtain detailed estimates of demand and cost, and then investigate the impact of product repositioning and price changes for cars assuming Bertrand competition. These results are very informative for strategic marketing mix choices and are possible because of the firm-level modeling of this industry.

However, in order to be more broadly applicable to the auto market, the estimation should allow for general forms of competition. For example, in a recent study, Sudhir (2001a) finds that firm behavior in the auto market indicate more aggressive behavior than Bertrand in some segments, but more cooperative behavior in other segments. Additionally, the nature of competition can vary in different periods. For example, research by Bresnahan (1987) suggests that competitive behavior changes depending on whether markets are in an expansionary or recessionary state. Such information about competition, when accounted for in "what-if" simulation models, will give managers a more accurate picture of the impact their choices of marketing mix and positioning strategies on profits compared to the original Bertrand assumption in Horsky and Nelson. A manager could also use these estimates to evaluate profitability implications of a merger between firms. For example, when Chrysler bought American Motors in 1987, it would have been possible to study the profit impact of such a merger using such estimates. Antitrust officials could have used such a model to evaluate the social welfare implications of the merger. In fact, Nevo (2001b) uses his estimates of a structural model of the cereal market to evaluate the profitability and social welfare implications of the merger between General Mills and Ralston Purina's branded cereal line (that included the Chex line).

In general the structural models enable us to better understand the sources of market power and profitability. (We had argued in the Section 1 that this is the fourth benefit of using NEIO models). This is useful for managers and anti-trust officials. Is the superior profitability of a firm due to its better ability to provide customers what they want (demand advantages), superior efficiency (cost advantages) or anti-competitive conduct (tacitly cooperative behavior)? Nevo (2001a) finds that the market power of firms in the cereal market can be best explained by the firms' demand advantages through differentiated products targeted to different segments of the market than by anti-competitive conduct.

Given these benefits of the NEIO approach, we believe that there are several applications of this to the empirical study of competitive marketing strategy. Thus far, much of the applied work in this area has been on market power, because these methods have been of great interest to researchers exploring antitrust issues. Some of the most pervasive findings have been that even in the most homogeneous of industries, there is significant market power if there is a sufficient degree of concentration. Bresnahan (1989) presents the Lerner indices for a number of markets based on prior NEIO studies. Firms also seem to be able to tacitly achieve cooperative conduct. As these methods diffuse through applied areas such as business strategy and marketing, there should be a rapid increase in empirical applications and we should be able to address issues of broader interest to business researchers. Researchers in marketing have already begun to explore many such issues. For example:

1. testing hypothesis about the nature of strategic interaction and relative power between manufacturers and retailers (Kadiyali et al., 2000; Sudhir, 2001b; Cotterill and Putsis, 2001);
2. analyzing change in competitive behavior among firms due to an entry into the product line by one of the firms; the impact of a private label on competitive interactions between manufacturers and retailer (Kadiyali et al., 2000; Putsis and Dhar, 1999; Cotterill et al., 2000);
3. retailer pricing objectives and behavior (Chintagunta, 2000; Sudhir, 2001b);
4. examining whether firms' cooperative or aggressive strategies are consistent with their long-term profit objectives (Sudhir, 2001a)

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Methodological innovations in estimating models of dynamics of competition, discrete strategy choice, and asymmetric information are expected in the near future, given the high degree of interest among empirical industrial organization economists. Perhaps a measure of this interest is the large number of high quality doctoral dissertations in this area from many prestigious economics departments. As the number of researchers in marketing interested in this area also increases, we hope the "gap between theoretical and empirical research in competitive marketing strategy" will become smaller. With enough new papers on issues of interest to marketers, we hope a meta-analysis of NEIO based industry and market-specific findings will also lead to generalizable conclusions from this literature.

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