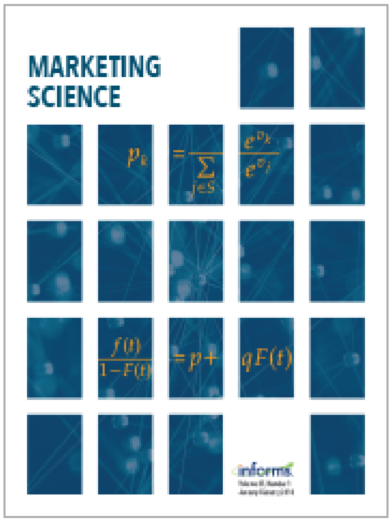

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Invited Commentary

Removing the Boundary Between Structural and Reduced-Form Models

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The authors provide a comprehensive and useful review of structural models in marketing (Chintagunta et al. 2006). They evaluate the strengths and limitations of a structural approach and present examples of recent advancements in the development and application of structural models. Their discussion on the directions for future studies is very insightful. Despite the growing trend in the literature to claim contribution by offering structural treatments to research questions, it remains arbitrary and sometimes mysterious as to what constitutes a "structural" model. I agree with the authors that artificial boundaries are commonly imposed in our field between structural and reduced-form models. I believe it is more constructive to classify research studies along a structural/reduced-form continuum than to draw a distinctive line between, or even develop different research paradigms around, them.

My objective in this discussion is to provide further insights into the structural/reduced-form continuum. I first argue that this continuum is usually multidimensional, and one can move up the continuum in two directions. Following the argument are some examples of how the studies in the literature can be positioned along the continuum. I also discuss the role of data in developing more structural models. I argue that limited data quality can be a "double-edged sword" for the use of more structural models and that data integration and researcher creativity can be substitutes for limited data quality. Directions for future research on moving up the structural/reduced-form continuum are also identified. The discussion intends to support the complementarity between "structural" and "reduced-form" models, and the need to break the boundary between them.

Although invited commentaries are not formally peer-reviewed and represent the opinion of the author, authors were carefully chosen based on their outstanding expertise in the areas of their respective commentaries.

1. The Structural/Reduced-Form Continuum

Empirical models are often compared in their efficiency to extract more information from data (Shugan 2002). The data of interest to researchers in marketing are often generated from some latent decision process.[1] The information extracted is usually used for policy evaluation. Policy-oriented models can be classified along a structural/reduced-form continuum. At one extreme are models that completely ignore the underlying decision process, but focus on the statistical relationships between variables (e.g., marketing-mix inputs and sales outputs).[2] There are two directions along which we can depart from this extreme and move up the structural/reduced-form continuum.

The first one lies in explicitly investigating the implicit assumptions, regarding the scope of the system of decision processes, that are necessary for statistical reduced-form models to yield consistent estimates. A noteworthy point, maybe the most important one in marketing that is essentially devoted to understanding the *interactions* among economic agents, is the recognition of the interactive roles of different decision makers in a market (e.g., consumers and firms). For instance, if we permit marketing mix (e.g., price) to be decisions made by firms, we can build up more structural models of both demand and supply (e.g., Villas-Boas and Winer 1999, Yang et al. 2003).[3] We can also expand the scope of consumer decision

[1] McFadden (1999) presents a framework of decision processes that translate perceptions, beliefs, affect, attitudes, preferences, and decision rules to outcomes through a "black box."

[2] See, for example, Pauwels (2004).

[3] Kuksov and Villas-Boas (2005) propose a method of simulated moments to test the endogeneity of firm behavior while accounting for consumer heterogeneity. See also Sudhir (2001), Villas-Boas and Zhao (2005), and Villas-Boas (2006) on models that integrate the decisions of consumers, manufacturers, and retailers.

making by recognizing that a behavioral response is usually governed by multiple decision processes. We can develop a more structural model by, for example, extending consumers' intertemporal decision-making horizon (e.g., Erdem and Keane 1996). Capturing sequential information transmission through observational learning (Zhang 2005), one can move a model further to the structural end of the continuum. Similarly, a model that incorporates the interdependence of purchase incidence and brand choice (e.g., Chiang 1991, Chintagunta 1993) is more structural than one that does not (e.g., Gupta 1988). We can further enhance the structure by capturing the interdependence of brand choice and quantity decisions (Hendel 1999, Kim et al. 2002, Erdem et al. 2003, Dube 2004). Note that these research efforts significantly improve both in-sample fit and out-of-sample predictive performance relative to their respective, less structural counterparts.

The second direction is due to the well-known argument by Lucas (1976) that any policy change that constitutes a major regime shift, by altering the structure and elements of the decision process (e.g., beliefs, information set, or contexts, etc.), can potentially lead to unstable responses. One can deal with this critique by delving into the underlying decision-making mechanism and explicitly modeling the decision primitives. The blessing belief is that the more fundamental the model's primitives are, the more stable the behavioral responses are. Research efforts along this dimension usually aim at decomposing the impacts of alternative behavioral or psychological incentives in driving a common response. A recent example involves using scanner panel data without consumption information to estimate the behavioral processes characterizing multiple variety purchases in a single shopping visit (Guo 2006). The first behavioral process is attributed to anticipated variety seeking (McAlister 1982). The second incentive is a consumer's desire to deal with preference uncertainty that is caused by the time lag between purchase and consumption occasions: Buying (and owning) different varieties allows for adjusting subsequent consumptions according to the realization of preference uncertainty, i.e., consumption flexibility (Kreps 1979). Standard discrete-choice models simply disregard this issue by assuming single-variety purchase (e.g., Chintagunta 1993). Some recent studies (Hendel 1999, Kim et al. 2002, Dube 2004) allow for multiple variety purchases without distinguishing the underlying behavioral processes. Walsh (1995) illustrates that these two behavioral incentives can lead to differential implications with standard scanner panel data. Guo (2006) incorporates Walsh's idea, which involves comparing the temporal versus horizontal purchase variations, into an integrated model of multiple variety choice. This study demonstrates that with a structural model it is feasible to directly capture the behavioral impact of consumption even without consumption observations.

It follows that there are no true structural models; there are only models that are more structural than others along either dimension of the structural/reduced-form continuum. Even the basic logit model of discrete choice bears a structural interpretation (McFadden 1974). It should also be clarified that a model does not necessarily impose more behavioral or parametric assumptions than its less structural counterparts. A model dealing with "multiple discreteness" actually relaxes the unrealistic assumption of single variety purchase during a shopping occasion (e.g., Hendel 1999, Dube 2004). In a model of both demand and supply, semi- or nonparametric methods (e.g., GMM) can be used to deal with the endogeneity issue, and equilibrium assumptions on firm behavior are not inevitable (i.e., the limited information approach). Models with more structure do not necessarily require a higher degree of optimality or sophistication in decision making, e.g., those that incorporate and even explain bounded rationality. Moreover, some criticisms of "structural" models (e.g., the ignorance of outside good, continuity of demand, fixed market size, etc.) applies equally to most reduced-form models in the literature.

2. The Role of Data

The need for more structural models for the purpose of policy evaluation boils down to a data issue. If we had sufficient variability in the data for the policy variable, the decision process would be reasonably approximated by the estimates in a statistical reduced-form model. When we believe that the policy analysis constitutes a major regime shift that is not sufficiently covered by the validation sample, we would go through the endeavor to look for more structure by relying more on the researcher's belief on the primitives of how the economic agents behave (Bronnenberg et al. 2005). For example, the trade-off between the limited- and full-information approaches has to balance our confidence in the quality of data (e.g., instruments) and our belief in the nature of firm interaction (e.g., equilibrium concepts).[4] However, one should be reminded that the data issue can be a double-edged sword—due to the well-known bias/efficiency trade-off. Estimating a model with more complex structure usually demands a higher degree of variations in the data for identification and/or efficiency considerations than a less structural model does.

[4] See Villas-Boas (2005) on comparing the limited versus full-information approaches for nonlinear models.

It is data (e.g, availability, scope, variation, etc.) that define the limit of the structural/reduced-form continuum. No structural model can extract information that is actually absent in a data set (Shugan 2002). With only aggregate data, for example, we cannot depart too much from a mixed logit model of demand with buyer heterogeneity (e.g., Nair et al. 2005). With purchase observations at the disaggregate level (e.g., scanner panel data), we can then move up the continuum to investigate the underlying decision processes. We can further augment the analysis if we have indicators of the underlying psychological constructs (e.g., stated expectations). Similarly, the absence of consumption data may limit our ability to investigate some interesting issues, e.g., preference time-inconsistency across the purchase and consumption stages, or consumers' stockpiling decisions (Sun 2005). Therefore, the value of a structural model should be assessed relative to the quality of available data.

There are substitutes for collecting (costly) more and better data. One solution is to integrate complementary data sets such that each data set's shortcomings can be offset by the others' merits. Researchers' intellectual efforts and creativity can also be used to enhance the efficiency in extracting information from the extant data. Chintagunta and Dube (2005) combine household panel data and store-level data to address the heterogeneity and endogeneity issues more efficiently. Another example is Guo (200y), who exploits the difference in a consumer's temporal versus horizontal variety purchases to capture the impact of consumption flexibility without the help of consumption data.

3. Moving Up the Continuum

The opportunities for future research to move up the structural/reduced-form continuum are numerous. One can investigate the processes characterizing the interdependence of various decisions, especially in a sequential setting. The existence of uncertainty about subsequent decisions may yield interdependence in the behavioral observations. For example, Bell and Lattin (2000) investigate the impact of brand choice on store visit, and Iyengar (2004) simultaneously studies consumers' cell-plan choice and usage behaviors. Their methods hinge on imposing some linkage on the parameters capturing each of the decisions. A more structural approach would be modeling the role of uncertainty directly (e.g., Narayanan et al. 2004, Guo and Erdem 2006). Similar issues can be seen in other contexts, e.g., bank-account opening and subsequent investment decisions (Li et al. 2005), or Web page visit and the following online purchase decisions.

Interesting issues can arise if we relax the price-setting assumption of firms. Chen et al. (2004) recognize that automobile retail prices are usually negotiated between dealers and consumers. Their structural model captures the bargaining process in determining the automobile price as well as the purchase decision in a transaction. In a different setting, Misra and Mohanty (2005) investigate structurally how wholesale prices are negotiated in a channel.

Another fruitful avenue appropriate for the structural approach is to investigate the role of marketing mix in a decision process. Researchers have long incorporated the impacts of feature and display in reduced-form models of brand choice (e.g., Guadagni and Little 1983). Recently, Mehta et al. (2003) proposed a structural model of display where consumers' (in-store) search costs could be reduced by displays, thereby increasing the probability of a displayed brand being included in the consideration set. Similarly, a structural model can be developed where features influence a brand's awareness and/or price information structure, which in turn affects the store visit decision. One can also investigate the differential impacts of price versus feature on a consumer's utility at the consumption versus purchase stage.

In summary, we should remove any arbitrary boundary between the so-called "structural" and "reduced-form" models. More structural methods can relax some assumptions on the scope of decision making in a market, and/or improve the stability in policy simulations by investigating the (assumed) primitives of how economic agents might behave. We should also recognize that the increasing information-extracting efficiency with a more structural model usually leads to more computational complexity. It is no doubt that a model with less structure is simpler to estimate, communicate, and disseminate. Therefore, it is important to leverage the complementary properties of different methods along the structural/reduced-form continuum in furthering our knowledge on important research questions.

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