BART J. BRONNENBERG, PETER E. ROSSI, and NAUFEL J. VILCASSIM*

Structural Modeling and Policy Simulation

A primary goal of research in marketing is to evaluate and recommend optimal policies for marketing actions, or "instruments" in the terminology of Franses (2005). In this respect, marketing is a very policy-oriented field, and it is ironic that so much published research skirts the issue of policy evaluation. Franses's article draws much needed attention to the question of what sort of model is usable for policy simulation and evaluation. Our perspective on what constitutes a valid model for policy evaluation differs from Franses's view, but we believe our view complements his in many important respects. We also strongly believe that marketing has much to contribute to the literature on structural modeling. We outline some of what we believe are the advantages for marketing scholars of using structural modeling for policy evaluations and some of the challenges presented by marketing problems.

Franses focuses on a reduced-form sales response model in which the outcome variable (y_t) is modeled conditional on marketing variables (x_t). If customers anticipate future marketing actions and take these into account in responding to the environment at time t, an additional equation is appended to the system to describe the evolution of the x_t variables. In Franses's view, this system can be used for policy simulation if both the y and x equations have time-invariant parameters. That is, the Lucas critique, which implies that parameters of reduced-form models change if the policy regime changes, does not apply. According to Franses, a model must pass standard diagnostics, possess good predictive properties, and exhibit parameter stability to be useful for policy simulation. We applaud the attention Franses is bringing to model diagnostics. We believe that structural work in both marketing and economics should pay close attention to the central features of the data. Increased use of model diagnostics will help ensure that structural models are capable of capturing these features. However, we do not believe that all the criteria proposed by Franses, such as out-of-sample validity and parameter stability, are either necessary or sufficient to render a model useful for policy simulation.

Reduced-form models can pass all diagnostics, including out-of-sample validation, and still provide misleading predictions about the effects of policy changes. Reduced-form models can exploit the well-known bias/variance trade-off explicitly to achieve excellent predictive performance. Because most investigators use predictive validation to calibrate or choose their model specifications, it is likely that reduced-form models have superior predictive performance relative to a structural model that is built using other criteria. Unless the policy regime changes, even out-of-sample validation cannot determine whether a model produces reliable forecasts of policy changes. For example, suppose we fit a model of sales regressed on regular price and a deal variable using data from a "high–low"-style market. This model could pass all standard diagnostics and provide excellent predictive validation. However, if we try to apply this model to everyday low price markets in which the same products are sold, we may dramatically underestimate the effects of regular price changes because consumers' response to long-term and short-term price changes depends on their expectations of the depth and frequency of deals. In summary, it is entirely possible for a structural model to have poor predictive performance relative to a reduced-form model and still be useful for policy evaluation.[1]

These points apply with equal force to tests for parameter variation. A model may appear to have time-invariant parameters simply because the policy regime has remained constant. Conversely, a model may exhibit parameter variation for reasons other than changes in policy. Smooth evolution of model parameters can create much needed flexibility in the model. This flexibility can be imparted to either a reduced-form or a structural model.

The bottom line is that standard predictive validation exercises are not sufficient to discriminate between models in terms of their usefulness for policy simulation. These standard predictive validation tests mostly determine the optimal point on the bias/variance trade-off frontier. However, we do not want to take this point too far. If a model has particularly bad in-sample or out-of-sample fit, it may be because the model does not capture some salient feature of the data. In this sense, we believe that prediction can be a useful tool to help sort among candidate structural models, even though predictive performance cannot answer the question of usefulness for policy simulation. However, what is required is a more demanding prediction exercise in which the marketing policy environment shifts. In some cases, variation in the policy regime may not be present in the data (particularly with highly aggregate data). In these cases, we must rely more on the confidence that we have

*Bart J. Bronnenberg is Associate Professor of Marketing, University of California, Los Angeles (e-mail: bbronnen@anderson.ucla.edu). Peter E. Rossi is Joseph T. Lewis Professor of Marketing and Statistics, University of Chicago (e-mail: peter.rossi@gsb.uchicago.edu). Naufel J. Vilcassim is Professor of Marketing, London Business School (e-mail: nvilcassim@london.edu).

[1]Subsequently, we formally define a structural model and argue why it is preferable to a reduced-form model for policy evaluations.

Journal of Marketing Research
Vol. XLII (February 2005), 22–26

properly specified the primitives of the model and that these primitives are policy invariant.

DEFINITION OF STRUCTURAL MODELS

A structural model begins with a view that observed behavior is the outcome of a decision process in which a consumer or firm makes optimal decisions based on a maximization of an objective function subject to resource constraints. This view is broad and not very limiting in terms of behavior. Much "irrational" behavior is only irrational relative to a specific objective function and constraint set. If sufficient latitude is allowed in the setup of the optimization problem, many behaviors are possible.

Demand-Side Modeling

Marketing begins with an understanding of the consumer. Therefore, most structural models begin with a specification of the consumer's objective function and constraints. It also requires that the modeler determine the decision variables for the consumer, the information set available to the consumer, the resource constraint, and the time horizon. For example, a "simple" demand model would specify a utility function over a set of consumption goods x and prices p and a budget constraint given income y. This problem could be written as follows:

$$\max_x u(x|\theta), \text{ subject to } p'x \leq y. \tag{1}$$

The solution to this problem is a decision rule, $x = f(p, y)$, which specifies how this particular consumer responds to price and income or expenditure allocation changes. The hope and assumption here is that the utility parameters (θ) do not change when prices change.

This model is a simple abstraction, which does not adequately describe the world. However, before this model is discounted completely, we should remember that much of the industrial organization and marketing literature is built on models that are not much more complicated than our model. We subsequently delineate ways that this model might be elaborated on to capture various important features of the marketing environment.

First, although price may be one of the most important instruments of marketing policy, it is not the sole one. Promotional and advertising variables can be entered into this model. A simple way to do so would be to make the utility parameters a function of these variables. However, advertising and promotional variables can also have more indirect effects through the information set of the consumer. In this simple example, the consumer is assumed to be fully aware of the marketing environment, which consists of the vector of prices. An important area of research is the structural modeling of the information set available to the consumer. If the consumer is not fully price aware, we might model the process by which the consumer "samples" or acquires price information (see Mehta, Rajiv, and Srinivasan 2003, 2004). The structural approach requires that we model the acquisition of price information as an optimal search process in which the consumer trades off the cost of additional price information with the benefits (as measured by higher levels of attainable expected utility). This approach also gives us a way to understand how certain types of advertising can be evaluated. In-store displays, for example, can be thought of as devices to provide lower-cost price information to the consumer.

Second, the simple demand model is a static or one-period model. Multiperiod data can be thought of as a sequence of one-period problems or the result of a more complicated dynamic model. A simple motivation for considering nontrivial multiperiod models is to recognize that we must separate the purchase and consumption decisions. In marketing data sets, we typically only observe purchase decisions. If we want to model purchase behavior, we must consider that consumers are purchasing products in anticipation of future consumption (see Dubé 2004; Erdem, Imai, and Keane 2003; Hendel 1999). Therefore, we must include an inventory accumulation and intertemporal budget constraint into a demand model. In this multiperiod model, consumers attempt to maximize the total or discounted flow of utility that is subject to inventory accumulation and budget constraints. This formulation requires some assumptions about the horizon of the decision process, as well as a specification of utility over multiple periods of consumption. For mostly reasons of convenience, these models are specified with a simple additive utility function and an infinite planning horizon. Finite planning horizons and nonseparable utility functions dramatically complicate the class of optimal decision rules.

Third, in a multiperiod model, it is important to specify the information set available to the consumer. At one extreme, we could assume that the consumer is myopic or totally ignorant of the future course of prices. At the other, we might assume that the consumer is omniscient and knows the entire future path of prices. Reality lies somewhere in between. The consumer has expectations of the future values of prices but can never be certain and therefore regards the path of prices as the outcome of a stochastic process. From a policy point of view, uncertainty about the future values of prices means that expectations of prices (as well as, possibly, other aspects of the price stochastic process) enter into the optimal decision rules. Demand at time t will depend not just on current prices but also on current inventory levels and expectations of future prices. The decision rule or demand function will be a function of the parameters of the stochastic process that governs prices. A policy change in this world involves a change in the parameters of the price process. The importance of the structural approach is that it provides reliable predictions of changes in demand as price process parameters change.

A reduced-form approach to dynamic demand models would be to specify a multivariate time-series model (such as a vector autoregression) for both the purchase time series and the time series of marketing instruments (e.g., price). This joint modeling does not ensure that predictions are immune from the Lucas critique. If we change the parameters of the price process, the parameters of the purchase process will change as well. Standard time-series models do not forge this explicit link between the two processes.

Fourth, price uncertainty is not the only type of uncertainty that may figure into multiperiod or dynamic settings. The consumer may also be learning about attributes of a product, such as its overall level of quality. Consumer learning also provides an explicit role for advertising as a means to provide information or quality signals. In a dynamic setting, the consumer updates his or her view of the product through some sort of Bayesian paradigm. For example, in Erdem and Keane's (1996) study, consumers learn about the quality of detergents through consumption and advertising. This learning aspect of consumer behavior gives rise to an experimentation motive by which the consumer may decide to sample a product whose expected utility at the current time is less than other available products (the multi-arm bandit problem). The problem with the standard Bayesian model of learning is that the posterior eventually degenerates on the true value of the parameter for which learning is required, which introduces a curious nonstationarity in which consumers are born ignorant but shortly become perfectly informed.

Fifth, another issue that is noteworthy with respect to demand-side modeling is the nature of the data available to the researcher, namely, individual versus aggregate. Although recent advances in data collection technology have increased the availability of high-quality individual- (or household-) level data, researchers still are more likely to have access to aggregate-level data (at the store, chain, or market level). The availability of data at the aggregate level may partly explain why researchers often use reduced-form models for demand specification. However, one of the more important recent developments in the modeling of demand has been the development of aggregate-level demand models that start from the microeconomic foundations of utility maximization at the individual level and then explicitly aggregate over a heterogeneous population of subjects to derive the aggregate demand function that preserves the economic primitives of consumer preferences. The resulting demand model is structural (Berry 1994; Berry, Levinsohn, and Pakes 1995; Nevo 2001).

This development of structural demand models that can be estimated from aggregate data has spawned many studies that examine various policy implications. For example, Chintagunta, Dubé, and Singh (2003) examine the firm profit and consumer welfare implications of a retailer adopting a zone pricing policy relative to uniform pricing. Likewise, Nevo (2001) examines the implications of mergers in the ready-to-eat cereal markets.

Useful as these models are as structural representations of demand, we caution that the blind application of them is also not appropriate. For example, the aggregate random-effects logit model has many desirable properties (e.g., is parsimonious, easy to estimate) and produces plausible results. However, in certain situations, a discrete choice logit model may not capture the true behavior of customers on any purchase occasion. In product categories in which consumers buy more than one brand/type/size/flavor and buy more than one unit on any purchase occasion, a discrete choice model may not capture the true underlying economic primitives of the consumer. Policy simulations based on such a model could lead to incorrect inferences.

Supply-Side Modeling

Given the many possible choices of information sets, utility functions, and constraints, models of consumer behavior alone can easily become extremely complicated. These models also present challenges for estimation. However, a demand model alone may be incomplete without additional modeling assumptions of firm behavior and market equilibrium. A complete model would specify a firm's objective function, as well as a model for the interaction between firms in markets with a small number of competing firms. There are several strong arguments for this point of view. First, the goal of marketing is to advise firms about the optimal setting of their marketing instruments. This advice requires a model not only of how consumers respond to changes in the firm's policy but also of how the firm's competitors will respond to its actions. Second, if the model of firm behavior and marketing equilibrium is correct, it can yield valuable information that, when imposed on the data, can produce more efficient estimates of the demand-side parameters. Finally, the strategic behavior of the firm may make it dangerous to condition simply on the values of marketing variables in estimating demand (see Berry, Levinsohn, and Pakes 1995; Besanko, Gupta, and Jain 1998; Bronnenberg and Mahajan 2001; Manchanda, Rossi, and Chintagunta 2004; Villas-Boas and Winer 1999; Villas-Boas and Zhao 2005). This challenge is known as the endogeneity problem. For example, as Villas-Boas and Winer (1999) emphasize, if there is a common demand shock and the firm sets the price with even partial knowledge of this demand shock, it may create a correlation between price and the demand error term.

Balanced against the advantages of modeling the supply side are several important considerations. Specification error in the supply side can result in substantial biases in the demand-side estimates. It is common to use a single-period Bertrand-Nash model of firm behavior. Because firms remain in business for more than one period and multiperiod models can give rise to a bewildering variety of possible equilibria, the assumption of a static Nash equilibrium might be misleading. Finally, a full model of demand and supply leaves little or no room for improvement in the existing set of marketing policies. That is, we assume that firms are behaving optimally and impose this assumption on our model. This status leaves the marketer with no prescriptive advice to give. In a sense, this discussion is an oversimplification, as we discuss in our concluding section.

Because of the problems with the specification of the supply side, there is growing sentiment to eliminate this part of the model and deal with possible endogeneity problems through instrumental variables. This solution, however, may simply be replacing one possible source of specification error with another. There are no general methods of ascertaining whether an instrumental variable is valid. Short of randomized experiments, there are no true instruments; there are only instruments that are more valid than others. Moreover, it may not be possible to determine logically whether a variable is a valid instrument without a model of (or at least perspective on) supply-side behavior. Another important problem is that many instruments have very limited variation, so it may be impossible to obtain reliable demand estimates with these weak instruments.

The supply side has received scant attention in the growing marketing literature on dynamic consumer models. Even the monopoly case has not been solved. For example, in a dynamic pricing model, it would be worthwhile to derive the optimal stochastic process for prices and explain the role of firm competition in determining these policies. On the advertising side, recent structural work by Dubé, Hitsch, and Manchanda (2004) addresses the problem of optimal dynamic policies with a realistic demand model. Nair (2004) considers the problem of intertemporal price discrimination, a problem long neglected in the empirical demand literature.

In this section, we have provided our definition of what constitutes a structural model. We should note that all structural modelers must make compromises regarding what phenomena are modeled using rigorous structural concepts. All empirical applications of structural models use reduced-form components, in that not all of the actual empirical specifications can be derived from optimizing behavior or in that some component of behavior is not modeled. We strongly caution our colleagues to refrain from the tendency to require that a model be comprehensive. In our view, it is much better to do a good job on a small part of the picture than to create an impossibly complicated or ad hoc model. Finally, we have emphasized that a "structural" model can focus primarily on the demand or supply side without including both. Endogeneity concerns are not the exclusive domain of structural models either. Not all structural approaches need to deal with endogeneity, and not all approaches to endogeneity need to be fully structural.

STRUCTURAL MODELING IN MARKETING: ADVANTAGES AND CHALLENGES

All too frequently, researchers in marketing are viewed as net consumers of work from other fields. In the structural modeling area, we believe that there is a real opportunity for marketing researchers to make unique and innovative contributions. This opportunity stems from our uniquely rich data, as well as our challenging set of problems.

Data in marketing are dramatically richer than those in economics in a variety of important ways. We have access to much more disaggregate data. (We use the term "disaggregate" broadly.) It is well known that we have rich panel data, but it is less well known or exploited that we have data on various different markets and/or firms at the same point in time. Modeling spatial aspects of these data is important, and understanding how changes in market structure and the consumer base affect firm behavior is an opportunity for marketers. We also can observe data on a huge variety of different products, which presents new challenges and opportunities for structural modeling. Solving the "location" or product positioning problem, as well as that of pricing and marketing existing products, is an exciting area. We also observe sales data at a relatively high frequency, which provides opportunities to study dynamics.

It is worthwhile to contrast the data-rich environment of marketing researchers with that of many researchers in the industrial organization area. A fair criticism of some work in that area is that elaborate structural models are used to overcome an inherent data limitation, such as the lack of quantity information, insufficient or nonexistent price variation, or the lack of disaggregate data. This comment is not intended to fault these researchers, but in marketing, we do not experience many of these data limitations.

Structural modeling has focused almost exclusively on behavioral or marketplace data, which are obtained by passive observation. There is another tradition in marketing that uses survey or experimental methods to make direct measurements of consumer utility. Because behavioral data are often not sufficient to identify the parameters of many complex structural models adequately, direct measurement methods might be used in conjunction with behavior data to tackle particularly tough problems.

Researchers in marketing often have access to wholesale price or cost data, which provide an additional source of information. More generally, researchers in marketing have greater access to information about firm behavior, which can be used to construct more realistic models of firm behavior.

Accompanying these rich data are a set of challenges that confront the structural modeler. Disaggregate data are fundamentally discrete, which means that standard continuous demand models are not adequate. Demand models that exhibit a mixture of interior and corner solutions are often required (Kim, Allenby, and Rossi 2002).

Marketers often do not have direct control over the marketing environment that their customers face. Thus, models of the distribution channel are often important. In turn, this opens new opportunities for testing models of market structure given the availability of data from the distribution channel. Historically, such data were often lacking (e.g., Sudhir 2001; Villas-Boas 2004).

Marketing decisions are made on different time scales. Pricing decisions may be made each week, whereas advertising and promotional decisions are made over a longer horizon (from six weeks to a quarter). Building a structural model that includes constraints on decisions or a rationale for these time frames is an exciting challenge.

The basic conundrum of positive economics—we assume that firms behave optimally so we have nothing to add in a normative sense—can be solved by careful attention to the information set available to firms. In economics, it is typical to assume that the firm knows the demand schedule perfectly. More work is required to consider the situation in which the firm behaves optimally relative to some information set and more information becomes available. For example, consider the situation in which the firm knows aggregate demand but has little information about individual consumers. If this information becomes available, it may present a profit opportunity for a firm that knows how to exploit it.

Managers follow various heuristics that deviate from optimal policies. One response is to modify the principles of optimal behavior (i.e., what has become known as behavioral economics). Another is to introduce various decision costs and/or uncertainties into the model to make a heuristic optimal. Little if any empirical work has addressed the latter approach (cf. Montgomery and Bradlow 1999).

CONCLUSION

We hope that Franses's (2005), Van Heerde, Dekimpe, and Putsis's (2005), and our articles will bring increased attention to structural modeling and policy simulation. Structural modeling is a difficult endeavor with many tradeoffs among realistic assumptions, econometric feasibility, and complexity. There is no one right approach, and we hope that researchers, reviewers, and editors will keep an open mind rather than establish a checklist approach to evaluating structural research. It is important to remember that the purpose of specifying and estimating a structural model is to make policy recommendations. Virtuosity in modeling is to be admired but only as the means to achieve the end of improvements in marketing actions. As the marketing field matures, we should anticipate more focus on policy experiments in the literature. Finally, we have emphasized that marketing has much to offer structural modeling, and we expect that some of the best work on structural modeling will come from the marketing side of the aisle.

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