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’ paper 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’ 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 will outline some of what we believe are the advantages for marketing scholars of using structural modeling for policy evaluations and what are some of the challenges which are 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 \( t \), then an additional equation is appended to the system which describes the evolution of the \( x_t \) variables. In Franses’ view, this system can then be used for policy simulation if both the \( y \) and \( x \) equations have time invariant parameters. That is to say, 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

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predictive properties, and exhibit parameter stability in order 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 of the criteria proposed by Franses, e.g. out-of-sample validity or 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 give misleading predictions about the effects of policy changes. In fact, reduced form models can exploit the well-known bias/variance tradeoff to explicitly achieve excellent predictive performance. Since most investigators use predictive validation to calibrate or choose their model specifications, it is likely that reduced form models will have superior predictive performance relative to a structural model which is built using other criteria. Unless the policy regime changes, even “out-of-sample” validation cannot determine if 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 “EDLP” markets in which the same products are sold, we may dramatically underestimate the effects of regular price changes. This is due to the fact that consumer response to long-run and short-run price changes depends on their expectations regarding the depth and frequency of deals. In sum, it is
entirely possible that a structural model may have poor predictive performance relative to a reduced form model and still be more useful for policy evaluation.  

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. On the other hand, a model may exhibit parameter variation due to reasons other than changes in policy. Smooth evolution of model parameters can create much needed flexibility in the model. This flexibility can be imparted either to a reduced form or 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 are mostly about determining the optimal point on the bias/variance trade-off frontier. However, we do not want to take this too far. If a model has particularly bad in-sample or out-of-sample fit, this 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 for this 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 if we have highly aggregate data). In these cases, we must rely more on confidence that we have properly specified the primitives of the model and that these primitives are policy invariant.

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2 We will shortly formally define a structural model and argue why a structural model is preferred to a reduced form model for policy evaluations
**Definition of Structural Models**

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

**Demand Side Modeling** Marketing starts with an understanding of the consumer. This means that most structural models start with a specification of the consumer's objective function and constraints. This 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

\[
\max_x u(x | \theta) \\
\text{s.t. } p'x \leq y
\]

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 \( (\theta) \) do not change when prices change.

Clearly, this model is a simple abstraction, which many feel does not adequately describe the world. However, before this model is discounted completely, we should remember than much of the I/O and marketing literatures are built on models which are not much more complicated than this model. We will delineate many of the possible ways in
which this model can be elaborated to capture various important features of the marketing environment.

First, price may be one of the most important but it is not the sole instrument of marketing policy. Promotional and advertising variables could be entered into this model. One simple way of doing this would be to make the utility parameters a function of these variables. However, advertising and promotional variables can also have more indirect effects through affecting 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, then we might model the process by which the consumer “samples” or acquires price information (see, Mehta et al. 2003, and Mehta et al. 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 of understanding how certain types of advertising can be evaluated. In-store displays, for example, can be thought of as a device to provide lower cost price information to the consumer.

Second, the simple demand model above is a static or one-period model. Multi-period data can be thought of as a sequence of one-period problems or as the result of a more complicated dynamic model. One simple motivation for considering non-trivial multiperiod models is to recognize that we have to separate the purchase and consumption decisions. In marketing data sets, we typically only observe purchase decisions. If we want to model purchase behavior, it can be argued that we must consider that consumers are purchasing products in anticipation of future consumption (c.f. Dubé 2004; Erdem, Imai
and Keane 2003; Hendel 1999). This means that we have to include an inventory accumulation and inter-temporal budget constraint into a demand model. In this multiperiod model, consumers attempt to maximize total or the discounted flow of utility 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 non-separable utility functions dramatically complicate the class of optimal decision rules.

Third, in a multi-period model, it is also 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. Clearly, reality is somewhere in between. The consumer has expectations of the future values of prices but can never be certain. This means that the consumer regards the path of prices as the outcome of a stochastic process. From a policy point of view, uncertainty about 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. This means that the decision rule or demand function will be a function of the parameters of the stochastic process governing prices. A policy change in this world involves a change in the parameters of the price process. The importance of the structural approach is to provide 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 VAR) for both the purchase time series as well as the time series of marketing instruments (e.g. price). It should be emphasized that 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 which may figure in multi-period or dynamic settings. The consumer may also be learning about attributes of a product such as its overall level of quality. This also provides an explicit role for advertising as a means of providing information or quality signals. In a dynamic setting, the consumer updates his view of the product via some sort of Bayesian paradigm. For example, in Erdem and Keane (1996), consumers learn about the quality of detergents via consumption and advertising. This learning aspect of consumer behavior gives rise to an experimentation motive in which the consumer may decide to sample a product whose expected utility at the current time is less than other available products (this is 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. This introduces a curious non-stationarity in which consumers are borne ignorant but will shortly become perfectly informed.

One other issue that is noteworthy with respect to the demand side modeling is the nature of the data that are available to the researcher, i.e. individual vs. aggregate. Although recent advances in data collection technology have increased the availability of high quality individual (or household) level data, it still remains the case that researchers 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 explain in part 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 by starting from the micro-economic foundations of utility maximization at the individual level and then explicitly aggregating over a heterogeneous population of individuals to derive the aggregate demand function that preserves the economic primitives of consumer preferences i.e. the resulting demand model is structural (see 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 cereals markets.

Useful as these models are as structural representations of demand, we caution that blind application of them is also not appropriate. For example, the aggregate random effects logit model has many desirable properties (is parsimonious, easy to estimate, etc.) 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 where consumers buy more than brand / type / size / flavor and buy more than one unit of quantity 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 can 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, some would argue that a demand model alone is incomplete without further modeling assumptions regarding firm behavior and market equilibrium. A complete model would specify a firm’s objective function as well as a model for interaction between firms in markets with a small number of competing firms. There are several strong arguments for this point of view. To start, the goal of marketing is to advise firms in the optimal setting of their marketing instruments. This requires not only a model of how consumers respond to changes in the firm’s policy but also how the firm’s competitors will respond to the firm’s actions. Next, if the model of firm behavior and marketing equilibrium is correct, this can yield valuable information that when imposed on the data can produce more efficient estimates of the demand side parameters. Finally, strategic behavior of the firm may make it dangerous to simply condition on the values of marketing variables in estimating demand (c.f. Berry, Levinsohn and Pakes 1995; Bronnenberg and Mahajan 2001; Manchanda, Chintagunta, and Rossi 2004; Villas-Boas and Winer 1999; Villas-Boas and Zhao 2005). This is known as the “endogeneity” problem. For example, as emphasized in Villas-Boas and Winer, if there is a common demand shock and the firm sets price with even partial knowledge of this demand shock, then this may create a correlation between price and the demand error term.

Balanced against the advantages of modeling the supply side are a number of 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. Given that the firms remain in business for more than one period and that multiperiod models can give rise to a bewildering variety of possible equilibria, the
assumption of static Nash 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 on our model. This leaves the marketer with no prescriptive advice to give. There is a sense in which this is an oversimplification and we will discuss this in our concluding section.

Given the problems with the specification of the supply side, there is growing sentiment for leaving out this part of the model. Possible endogeneity problems are dealt with using instrumental variables. This however may simply be replacing one possible source of specification error with another. There are no general methods of ascertaining if 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 if a variable is a valid instrument without a model (or at least perspective) on supply side behavior. Another important problem is that many instruments have very limited variation so that 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 is not worked out. For example, in a dynamic pricing model it would be interesting 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 et al. (2004) has begun to address the problem of optimal dynamic policies with a realistic demand model. Nair (2004) considers the problem of inter-temporal 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 point out 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 specification can be derived from optimizing behavior or in the sense 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 a “structural” model can be focused primarily on 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 there is a real opportunity for researchers in marketing to make unique and innovative contributions. This opportunity stems from our uniquely rich data as well as our challenging set of problems.

The data in marketing are dramatically richer than in economics in a variety of important ways. We have access to a great deal more disaggregate data. We use the term “disaggregate” very broadly. It is well known that we have rich panel data but it is less well known or exploited that we have data on a number of 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 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 means opportunities for studying dynamics.

It is interesting to contrast the data rich environment of marketing researchers with that of many researchers in the I/O area. A fair criticism of some work in that area is that an elaborate structural model is used to overcome an inherent data limitation such as lack of quantity information, insufficient or non-existent price variation, or lack of disaggregate data. This is not to fault these researchers but, in marketing, we do not have many of these data limitations.

Structural modeling has focused almost exclusively on behavioral or marketplace data. These data are obtained by passive observation. There is another tradition in marketing which uses survey or experimental methods to make direct measurements of consumer utility. Given that behavioral data are often not sufficient to adequately identify the parameters of many complex structural models, 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 provides 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 this rich data are a set of challenges which stretch 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 (c.f. Kim et al. 2002).

Marketers often do not have direct control over the marketing environment that their customers face. This means that 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., Villas-Boas 2004).

Marketing decisions are made on different time scales. Pricing decisions may be made each week, while advertising and promotional decisions are made over a longer horizon from 6 weeks to a quarter. Building a structural model which 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 is behaving 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, this may present a profit opportunity to a firm that knows how to exploit it.

It has been widely observed that managers follow various heuristics that deviate from the optimal policies. One approach 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 which make a heuristic “optimal.” Little if any empirical work has been done with the latter approach. (c.f. Montgomery & Bradlow 1999)

Conclusion
We hope that Franses (2005), Van Heerde et al. (2005) and this paper will bring increased attention to structural modeling and policy simulation. Structural modeling is a difficult endeavor with many trade-offs between 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 establishing a “check list” approach to evaluating structural research. It is important 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 the end of improvements in marketing actions. As our field matures, we should see more focus on policy experiments in the literature. Finally, we have emphasized that marketing has much to offer to structural modeling and we expect some of the best work on structural modeling to come from the marketing side of the aisle.
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