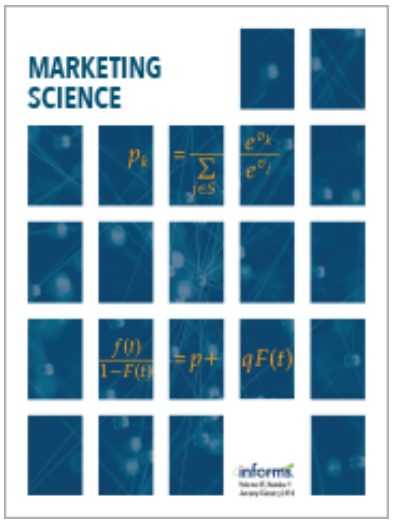

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Invited Commentary

Commentary on Structural Modeling in Marketing: Review and Assessment

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Chintagunta, Erdem, Rossi, and Wedel (2006) (CERW) discuss many different issues related to the use of structural models in marketing. They use examples of structural models that involve both consumer demand and supply-side competition to provide a critical assessment of the strengths and weaknesses of structural modeling and its future in marketing. While they have done a very nice job, the purpose of this commentary is to provide additional discussion of the three issues raised in their paper.

1. Strengths and Weaknesses of Structural Modeling

CERW observe that most structural models make strict parameterization and behavioral assumptions, and view this as a major weakness. I have two comments on this observation: First, parameterization is a way to approximate the demand surface or the nature of competition. As in reduced-form models, we can modify the functional specification to better fit the data, if necessary. With the availability of disaggregate data and the development of new estimation techniques, identification and computation burdens are further reduced, and less strict assumptions can be made in our models.

Second, I regard the fact that behavioral assumptions are explicitly laid out as a major strength. It makes the relationship between assumptions and estimation equations clear. This provides a direction for altering the model to match the specifics of a particular category (see a similar discussion in Pakes 2003). For example, Kim et al. (2002) model household purchase of multiple brands in a category as variety-seeking behavior, while in a different category Dube (2004) assumes that multiple-brand purchase behavior is generated from stochastic preferences during different consumption occasions. External data can be used to decide which assumption is more appropriate when applied to other categories. We may attempt to improve their models by considering other behaviors (e.g., Dube's model may be enriched by including variety-seeking or other state dependence behaviors). As for any model, structural assumptions may not fully describe the complex real world—the point here is how we can improve the quality of our approximations, and model the data in a sensible way in order to predict the impact of drastic regime changes—new product introductions, technology breakthroughs, or entry and exit phenomena.

2. Validation

Reduced-form models are validated by traditional test statistics such as within-sample or out-of-sample fit; these approaches may not be applicable to structural models. Model validation has received attention from empirical economists in recent years. For example, Bajari and Hortacsu (2005) use first-price auction data from lab experiments to test alternative structural model assumptions and find that participants exhibited risk-averse Bayes-Nash behavior. Todd and Wolpin (2003) use field experiment data to validate a dynamic behavioral model of child schooling and fertility. These exercises should also be important for structural modeling in marketing, because its underlying behavioral assumptions are always criticized by skeptics as unrealistic.

It is also important to note that poor validation may result from either incorrect behavioral assumptions, incorrect parameterization, or both. The explicit behavioral assumptions required by structural models are strengths in this regard, because they may be useful in determining whether the assumptions or the parameterization is incorrect. This is critical if we want to predict the impact of drastic regime changes. For example, assume an indirect utility function of consumer i for product j at purchase occasion t in a discrete choice model as follows:

$$u_{ijt} = x'_{jt}\beta_i - \lambda_i p_{jt} + \varepsilon_{ijt}, \quad (1)$$

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.

where x is a vector of product attributes and p the price. Similar to random coefficient models, we make parametric distribution assumptions for $\{\beta_i, \lambda_i\}$, say, $F_\beta(\theta_1)$ and $F_\lambda(\theta_2)$, to address consumer heterogeneity. Note that we rely on historical data, which may not have much fluctuation, to recover these distributions. Suppose we then want to use the estimates to predict changes in consumer choices when a new product k with drastically different x_k and p_k is introduced. The validity of this exercise depends on how well our distributional assumptions approximate the true unobserved heterogeneity, especially for those consumers who are outliers in F_β and F_λ (because product k may only attract those consumers). If not, we will get wrong predictions even if the behavioral assumptions underlying the structural model are correct (see Sonnier et al. 2005 for an example of this phenomenon).

3. Using Multiple Data Sources

CERW discuss the possibilities of allowing for limited information for decision makers, as well as relaxing some commonly made behavioral assumptions in order to improve the richness and interpretation of structural models. They also discuss the need for multiple data sources such as survey data on expectations to achieving these purposes. This is important: One of the major reasons that we make strict assumptions is due to model identification. To use a simple illustration, assume a (parameterized) market demand function for product j:

$$y_j = y(X_j, z_j, \omega_j; \Theta), \tag{2}$$

where y_j is the observed market demand, X_j a vector of the observed product attributes and other variables such as the competitive forces, z_j the observed decision variables (advertising expenditures, prices etc.), ω_j the stochastic component, and Θ a vector of demand parameters to be estimated. We obtain estimates $\widehat{\Theta}$ from our data. Suppose we allow for a different information set for a manager when making decisions for z_j. We may assume her *expected* market demand function as follows:

$$y_j^0 = y(X_j, z_j, \omega_j^0; \Theta^0), \tag{3}$$

where $\{\omega_j^0, \Theta^0\}$ are managerial expectations corresponding to $\{\omega_j, \Theta\}$ in (2). Further, assume that z_j comes from maximizing a parameterized managerial objective function as

$$V(z_j; X_j, W_j, \omega_j^0; \Theta^0, \Psi^0), \tag{4}$$

where W_j is a set of variables excluded from the demand function (e.g., cost variables), and Ψ^0 another set of parameters to be estimated. It is clear that, under this set-up, one cannot separately estimate parameters Θ^0 from Ψ^0 using data $\{y_j, z_j, X_j, W_j\}$. To identify model parameters, we impose restrictions by assuming that $\Theta^0 = \widehat{\Theta}$, and usually also that the form of V (hence, also Ψ^0) is consistent with a profit-maximization assumption. These assumptions may not be realistic, because the manager's information set is different from the researcher's (manager uses her prior experience to predict market demand as opposed to researcher, who uses ex post observed demand). Also, the manager may not be a pure (static or dynamic) profit maximizer due to principal-agent problems, government policy restrictions, or other organizational objectives. Consistent with CERW's idea, if the managerial *expectations* data y_j^0 is available, we may use that to estimate from (3) and then plug them into Equation (4) to infer $\Theta^0\Psi^0$ in the objective function. This allows us to relax the above-mentioned restrictive assumptions. One empirical example is provided in Chan et al. (2005). They use expectations data on ticket sales for each show in a nonprofit art-performance theater to recover managerial estimates of the attractiveness of various show attributes. Using the estimates, they further estimate the managerial objective function from an advertising decision model. They find that managers overspent in advertising in general and particularly for avant-garde shows, and provide some intuitive rationale for why the results are inconsistent with the pure profit-maximization assumption.

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