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Invited Commentary

Dynamic Structural Consumer Models and Current Marketing Issues

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Structural models integrate behavioral and psychological decision theory into economics models and are more aligned with the true underlying economic primitives of the consumers. This allows researchers to investigate more behavior-driven and process-oriented customer decision processes such as learning of product attributes, formation of a consideration sets, stockpiling, and flexible consumption that cannot be easily handled by traditional marketing models. Chintagunta et al. (2006) gives an excellent review on the development and applications of structural models in marketing for modeling both consumer demand and firm competition.

Recent interests in consumer research have diversified from frequently purchased packaged goods to services, high-tech, Internet, and information industries. Consumers are observed to be more sophisticated, long-term oriented, risk averse, and rational when making purchase and consumption decisions in these product categories. Structural models are better choices to capture the nature of the sophisticated decision process under the new marketing environment and engineering. Given the thorough review of Chintagunta et al. (2006), I will focus only on the dynamic structural demand models that have the components of information processing, rational expectation, and/or endogenous decisions to trade off current and future utilities, and I discuss some current marketing issues that can be most appropriately addressed by these models.

Key words: structural model; information processing; rational expectations; optimal decision; hyperbolic discounting; information asymmetry; signaling; searching; learning; e-commerce; dynamic and interactive marketing intervention; decision support system

1. Heterogeneity of Rational Behavior and Targeted Marketing

It is commonly assumed that every consumer discounts future utilities at the same discount rate. There is a need to test this assumption to enhance the behavioral richness and interpretation of these models (Chintagunta et al. 2006). An understanding of which segment, under what situation, and for which product categories consumers are more likely to be strategic provides guidance on consumer segmentation and targeting strategies. This is especially true for marketing financial products and high-tech products that require later purchases of add-ons. For example, in the credit card industry, sophisticated consumers are observed to take advantage of the "free interest introductory offers." They strategically manage payments to avoid interest charges and late fees. As a result, they are cross-subsidized by myopic consumers who pay those fees. Similarly, Gabaix and Laibson (2005) show that in managing high-tech products (e.g., printer) with add-ons (e.g., toner), firms exploit myopic consumers through marketing schemes that shroud high-priced add-ons. In turn, sophisticated consumers exploit these marketing schemes by pooling themselves with myopic consumers, receiving the loss-leader base good and substituting away from the add-on. With the presence of both myopic and sophisticated consumers, firms will choose not to educate the public about the add-on market, even when advertising is free.

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2. Hyperbolic Discounting and "Promotion Dynamics"

Another simplifying assumption is that consumers discount future utility at a constant exponential rate and future selves commit to the plan made by today's selves. However, behavioral research has shown that some consumers tend to consider only the immediate utility and disproportionally underestimate future consequences ("time inconsistency"). As a result, their actions frequently violate the plan they made previously ("self-control problem"). This intra-individual variability in time discounting is labeled as *hyperbolic discounting* (Loewenstein and Prelec 1992). Hyperbolic discounting helps explain many interesting marketing phenomena. For example, in an experimental study, Zauberman (2003) shows that consumers are reluctant to move from Amazon.com to a better website because they are unable to fully anticipate the impact of future switching costs and have the tendency to just avoid immediate switching costs. This explains the procrastination of switch that leads to consumer lock-in. Similarly, the use of credit cards stimulates purchase because it allows consumers to frontload consumption and delay payments (Soman and Cheema 2002). However, hyperbolic consumers are more likely to constantly delay their payments and accumulate debt because they cannot commit their future selves to the payment plan made at the time of purchase. Recognizing "time inconsistency" and the "self-control problem" provides marketers with novel opportunities to fine-grain dynamic structure of price, promotion, and payment plans—for instance, the design of rebate terms to improve purchase and discourage redemption.

3. Evaluating "Intertemporal Promotions"

We currently observe many companies adopt price and promotion schemes that intentionally separate promotion from purchase (e.g., credit card payment, buy-now-pay-later, rebate and reward programs) and purchase from consumption (e.g., subscription fee and annual membership). These are labeled as "intertemporal promotions" that require consumers to be able to look into the future for these price and promotion tools to be effective (Sayman and Hoch 2005). For example, a frequent-shopper reward program is designed as a promotion strategy that encourages customers to accumulate (current) purchases to obtain a (future) reward. Similarly, the pricing strategy adopted by online DVD rental (e.g., Netflix) is framed as a payment for the right to consume a certain amount of services in the future. Furthermore, the popular loyalty programs of airlines, hotels, and car rental industries allow consumers to choose when and at what level to claim the reward. Acceptance of a reward becomes an endogenous decision that is driven by future purchases (Kopalle et al. 2005). Given the increasing popularity of intertemporal price and promotion programs, it might be interesting to evaluate how the design (e.g., reward amount and distance between reward levels) of these programs (Shugan 2005) affects consumer choices. Dynamic structural models could be the most parsimonious approach to capture consumers' complicated intertemporal decision making.

4. Modeling Unobservable Consumer Decisions

Another advantage of the structural model is that consumers are assumed to derive optimal choice according to a specified decision rule using current information. It is possible to derive consumer-endogenous decisions that are known to the consumers, but unobservable to researchers, and study their statistical inferences. This opens avenues for many interesting studies that are not possible with reduced-form models, most of which require the decision variable to be observable to the researchers. For example, in a dynamic structural model applied to packaged goods, Sun (2005) studies the consumption pattern of consumers and shows how it is driven by current and future promotion, inventory, and purchase. She establishes the importance of recognizing the endogenous consumption in improving the measurement of promotion effect on purchase.

5. Information Asymmetry, Signaling, and Searching in E-Commerce

One distinctive characteristic of electronic commerce is the separation of buyers and sellers (Lucking-Reiley 2000). Without being able to physically examine the product, consumers face much more severe uncertainties in e-commerce. This information asymmetry can be relieved by sellers providing signals and buyers learning and searching for additional information on the Internet.

Structural signaling models have been developed to solve the signal extraction process to determine how much to revise consumer estimate of product quality (e.g., Erdem et al. 2006). Consumer search models have also emerged to investigate how (rational) consumers weigh the costs and benefits of search and how they examine its implications on price dispersion (Sorensen 2001). With the rise of the Internet, a number of authors have adopted these models to test the implications of lower search costs and higher penetration rate of Internet search engines. For example, Brown and Goolsbee (2000) find that proliferation of comparison sites has reduced the prices of life insurance policies.

Empirical research has shown that consumers are highly strategic with their bidding strategies in Internet auctions (Bajari and Hortacsu 2005). Internet auctions have become experimenting fields for researchers to test various rational and strategic behaviors. Dynamic structural models have been developed to study the search of product, formation of willingness to pay, optimal entry time, and frequency of revising bids. Recent papers in marketing draw implications on how sellers can better signal their product quality to alleviate information asymmetry (Park et al. 2005, Li et al. 2005).

6. Dynamic Marketing Interventions and Firms' CRM Decision Support System

Most of the existing structural models are applied to the frequently purchased packaged goods industry. Consumers are treated as decision makers, and managerial implications are implicitly discussed based on estimated demand models. Similar models can be extended to firms' decisions of customer relationship management (CRM) strategies and explicitly derive customer-centric and proactive marketing interventions (Sun et al. 2006).

From the firm's perspective, CRM interventions decisions (such as pricing, service assignment, or promotion campaign) are solutions to a stochastic dynamic programming problem under demand uncertainty in which the firm needs to learn about evolution of consumer demand, the dynamic effect of its marketing interventions, heterogeneity of customer preferences, the cost of acquisition, and long-term payoff, with the goal of maximizing "long-term" profit of each customer. For example, Sun and Li (2005) formulate the call allocation decisions of a service center as a CRM problem in which the company learns the heterogeneity of customer preference and makes optimal allocation decisions that best match customers with the appropriate center.

Today's information technology allows the firm to retrieve real-time customer information, automatically analyze customer insights, respond directly to customer requests, and provide customers with a highly customized experience. This increases the application of decision-support systems in CRM. This trend calls for researchers to develop solid learning and optimization routines to facilitate CRM decisions.

In summary, the above listed issues are examples of marketing problems that can be more conveniently addressed by structural models. As stated by Keane (1997) and Sun et al. (2003), it is natural to start by developing a theory of consumer decision process and then derive the implied statistical model. The assumption of rational expectations has been criticized primarily because it seems unlikely that people actually go through the calculation to process extensive information, form rational expectations, and make optimal decisions. However, experimental research has shown that consumers manage to make such choices swiftly because they use simplifying heuristics (Gärling et al. 1997). A good heuristic is consistent with an optimal solution to a structural model (Houser and Winter 2004). Under many circumstances, it is most appropriate and even parsimonious to use structural models to capture the information processing and optimal decision heuristic. The application of these models was hindered because of the complication of estimation. Recent advances in econometric techniques and computing technology significantly facilitate the applications of structural models. With the review of Chintagunta et al. (2006) and the complementary discussion of this paper, we hope for more marketing issues to be analyzed by structural models.

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