Response Models, Data Sources and Dynamics

Commentary on Albuquerque and Bronnenberg

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It is my pleasure to provide some perspectives on this article, and more generally on the research stream in marketing science on integrated demand and supply modeling. I will start by highlighting the specific contributions of the article I found most interesting. Then I will discuss some limitations and I will describe how these may be overcome by alternative research methods and data sources.

Albuquerque & Bronnenberg's stated objective is to "study the behavior of consumers, dealers, and manufacturers in the car sector and present an approach that can be used by managers and policy makers to investigate the impact of significant demand shocks on industry profits, prices, and market structure." That is an ambitious undertaking, as it aims to create relevance and credibility with distinct audiences, viz. academics, managers and government agencies. These audiences have different value systems, for example academics favor *generalizability* (broad applicability of the research methods and findings) and managers value *context* (capturing the richness of the specific problem at hand). Following the INFORMS mantra "the science of better", I take the viewpoint that the ultimate *raison d'etre* of this research is the improvement of managerial and public policy decisions. Descriptive models of agent behavior (in this case consumers, manufacturers and dealers) play an important role in this enterprise, but they are not the end goal. As such my comments will focus on the opportunities for influencing management and public policy practice.

In this context, the Albuquerque & Bronnenberg article performs remarkably well. The article systematically and thoroughly examines the behavior of the market participants, based on established economic primitives, and estimates the resulting equations using state-of-the-art econometric methods. In particular, the authors demonstrate ingenuity in their choice of response and cost estimators, based on both statistical and economic principles. Finally, the completeness of the model allows the researchers to examine some scenarios of interest to business and public policy, such as their estimate of the two-third pass-through effect on consumers of the "cash for clunkers" government subsidy in 2009, and their assessment that the 30% drop in US car demand due to the recent recession resulted in an 11% annual drop in car prices. Of particular relevance is the authors' inclusion of spatial competition, i.e. the combined influence of "brand" attributes (at the manufacturer level) and "location" attributes (at the dealer level) on consumer utility. As such, the paper takes market response modeling to a higher level of realism and relevance, which is no small accomplishment.

I conclude that this research succeeds in its first, descriptive goal, as the paper clearly makes incremental scholarly contributions. The second and third goals require more scrutiny, as their intended audiences are different. In particular, some empirical findings in the paper may be viewed as "straightforward" to managers in the sector. For example, dealers and manufacturers likely have first-hand experiential knowledge of competition between dealer locations, without the use of formal spatial models. When deteriorating demand conditions force dealer closures, it should not be difficult for a manufacturer to meaningfully rank order the candidates. On the other hand, the authors' estimation of the net effects on consumers and dealers of a government stimulus program should be a novel and important insight for all audiences. In this applied context I will discuss, in turn, the role of assumptions, the expansion of information sources, the importance of model validation and the study of intertemporal decision making.

1. *Assumption dependency.*

The authors are careful to state the assumptions underlying their models. By my count, there are 21such formal assumptions in the paper, 17 with respect to agent behavior and 4 statistical assumptions. This count demonstrates the "assumption dependency" of structural models that are empirically implemented. The consumer behavior (demand) assumptions such as utility maximization are generally accepted, and since purchase observations in this B2C context are abundant (over 15,000 in this case), they lend themselves to empirical testing as needed.

By contrast, the dealer and manufacturer (supply) behavior assumptions such as profit maximization may be more restrictive. This is an area in need of further research. Supply and pricing decisions are strongly context dependent, in particular the context of the time period in which the decisions are made. For example, car makers have annual production goals and sales quota, and the extent to which actual demand tracks toward these quota is a principal driver of their behavior. In addition, as auto manufacturers are publicly held firms, they face quarterly and annual financial disclosure requirements that can influence their decision making, in some cases leading to myopic behaviors (Mizik 2010). In sum, the assumption that suppliers are perennially in profit maximization mode needs more scrutiny, especially when the model results are applied to a holdout sample that represents a severe economic crisis.

From an econometric perspective, the context dependency of automotive decision rules can be handled with time-dependent or state-space models, in particular those that accommodate demand forecasts, capacity utilization and model-specific sales quota. This has been done in an automotive setting, for example by Roy et al. (1994), who developed optimal pricing rules for leader and follower car makers that incorporate demand forecasting models and forecast errors.

2. Expansion of information sources.

The paper follows an established tradition in industrial organization research of distinguishing between observations known to the researcher and the economic agents, and observations known only to the agents. That "information deficit" then leads the researcher to make economic behavior assumptions in order to identify the unobserved influences in the model. This is standard practice in the economics literature but, in my view, less useful in a marketing science context, for two reasons. First, it has been shown that the combined use of database models and managerial intuition provides results that are superior to the use of either in isolation (Blattberg and Hoch 1999). Second, more value will be created when research insights are "new to managers" as well as "new to researchers" (Bucklin and Gupta 1999).

Some survey research on managers can clarify the economic motivations on the supply side and result in models that are easier to estimate and enjoy higher face validity. As an example, Steenkamp et al. (2005) completed 52 manager interviews on the nature of their retaliatory behavior when their brands are attacked by competitive promotions and advertising. The high response rate to this survey (37%) illustrates that managers are quite willing to discuss their decision motives, at least in an anonymized context. These interviews led to conclusions that helped specify the models and corroborated the theoretical and econometric findings in the article.

In addition, supply-side data are becoming available through web based aggregators, notably in the automotive sector. Furthermore, when the firms under study are publicly held, their stock prices provide important external estimates of their future profitability, and these data are just as easily observable to researchers as they are to consumers and managers. Data on *investor response* have been used successfully to interpret managerial moves as either value enhancing or value destroying (see Srinivasan & Hanssens 2009 for a review).

In conclusion, it is increasingly possible to test and/or relax several of the economic-behavior assumptions by new data sources that will significantly enhance the acceptance and usability of structural models by managers.

3. Model Validation

The paper uses three forms of model validation: 1) the usual in-sample validation, for example against models without price endogeneity control, 2) a cross-sectional out-of sample test using several ZIP codes that were not used in estimation, and 3) a "reasonable results" test by comparing the model estimates to those reported in popular media that have industry expertise, such as published articles in the *Wall Street Journal*, the *Detroit Bureau* and the *North American Dealer Association*.

These validation runs are impressive, but they don't have the benefit of specific benchmarks that would be expected for application in industry. For example, we do not really know that a 0.79 correlation between actual and predicted market shares is a "good hold-out validation result," especially since there is no time split in this test. On the other hand, the authors' also used their model, estimated on 2004-2005 data, to predict some dealer closings after 2008. That is an unusual and persuasive holdout test on two of the seven brands in their sample. It would be very informative to see the model's accuracy on all seven brands' dealerships.

I emphasize these validation alternatives because, in my experience, the standards for model validation are higher in industry than in academic publications, in part because industry faces risks in using models for decision making that academics don't have. The most straightforward and accepted validation exercise is the controlled experiment. For example, the B2B buyer behavior model in Kumar et al. (2009) was validated with an experimental design that led to the remarkable insight that a customer approach to personal selling - as opposed to a traditional product approach - could simultaneously increase sales, lower costs, increase profits and increase customer satisfaction.

Controlled experiments are not realistic in many empirical settings, including the present study. However, non-experimental models can be validated based on the important principle of *forecast superiority*, which is often overlooked in economics-based modeling. In this case, a simple time-series extrapolative model of behavior can be used to establish a predictive performance benchmark. Then the value of structural knowledge is assessed by the degree to which the structural model beats the extrapolative model in forecast accuracy. Such tests are often based on the principle of Granger causality. In short, X Granger causes Y with respect to the information set containing X and Y if the forecast error of the model Y=f(past Y, past X) is lower than that of the model Y=f(past Y). As an application in the automotive sector, Roy et al. (1994) established empirically that Ford acted as a Stackelberg price leader in a segment of the market by conducting Granger causality tests on price movements. From a marketing substantive perspective, Granger causality tests help establish the economic and managerial value of collecting additional data and building more complex market response models.

4. Exploring the time dimension

In their conclusion, the authors acknowledge that intertemporal decision making is absent from their model, and leave that as an important area for future research. Indeed this time dimension is essential, in part because actions that take place under stationary vs. evolving conditions can have widely different impact on demand and profitability (e.g. Dekimpe and Hanssens 1995). For example, it has been shown in both the consumer products and automotive sectors that about two thirds of weekly time periods reflect business conditions that are stable, with the remaining one third either improving or deteriorating (Pauwels and Hanssens 2007). The most pivotal time periods for a business, i.e. those when a deteriorating situation is turned around, represent only one to six percent of weekly observations. If marketing and other supply actions can cause performance turnarounds (as shown in the article), then future research should focus on such *punctuating equilibrium* conditions, as they imply that future outcomes are path dependent. Various dynamic models may be used for that purpose, including cointegration and vector error-correction models, Kalman filters and dynamic linear models at the aggregate level, and agent-based models at the individual level. I refer to Leeflang et al. (2009) and Rand & Rust (2011) for comparative reviews of time-series methods and agent-based models, respectively.

For research endeavors that combine demand and supply drivers, systems of time-series equations are particularly appealing (e.g. vector autoregressive models, vector error-correction models, dynamic linear models). Separate equations are specified for the behavior of consumers, manufacturers, distributors, competitors and, in some cases, investors. The equations may or may not incorporate certain equilibrium conditions among the variables, and tests are available on the existence of such equilibria. The estimation requires extensive databases over time, and possibly across markets (e.g. in panel VAR models). The major strength of such system-dynamic models is that they readily incorporate feedforward and feedback loops (i.e. endogeneity) and are specific about intertemporal response behavior. For example, impulse-response functions show how the long-term system's response to a shock builds up or dies out. As marketing databases become increasingly granular – for example from monthly to weekly to daily data – these methods gain in relevance and applicability.

In the present context, the authors' analysis of demand shocks demonstrates how the evolution of automobile demand is critically important for dealer and manufacturer profitability. But what constitutes a demand shock? The authors define it as a sustained, two-year drop in car demand, simulated as an increase in either the utility of consumers' outside good, or in their price sensitivity. When this occurs, diligent car manufacturers will update their demand forecasts quickly, for example with the help of weekly car sales reports issued by third-party data aggregators. A prolonged slump in demand would not be a shock for very long, and both dealers and car makers would at least have the capability to initiate corrective actions, including adjustments to their product portfolio, to advertising spending, pricing and dealer incentives. *Reaction time* and *reaction effectiveness* thus become important determinants of manufacturers' and dealers' revenue and profitability. They can be estimated with dynamic response models, which are outside the scope of the present study.

Furthermore, if automobile manufacturers were slow to recognize these new prevailing demand conditions, their investors would motivate them to act more quickly. We know that, at the investor level, all value-relevant shocks are *reflected* in stock prices immediately, and are *fully* incorporated over a relatively short time period. As an example, again in the automotive sector, Pauwels et al. (2004) estimated that new-product introduction *shocks* take six to eight weeks to be fully incorporated in the manufacturer's future earnings outlook, i.e. its stock price. This observable reaction is much faster than the time to peak consumer adoption or the time till the next new-model launch (typically about six years, with a minor face lift after about three years). In conclusion, investor response is an important and overlooked source of information on the long-term profit impact of demand shocks, and can readily be incorporated in dynamic models.

In conclusion, the Albuquerque & Bronnenberg article provides a convincing demonstration of the power of integrated demand and supply modeling in marketing. Their models are analytically rigorous and, when applied to high-quality data, create opportunity for important managerial and public policy insights. My comments have focused on four areas of future research that will enhance the strategic value of such structural models: explore new data sources to reduce the researcher's "information deficit" relative to that of managers, use data and models from the operations, finance and accounting fields to make the models more context relevant, create prediction based model validation to gain managerial acceptance, and use dynamic models to study intertemporal behavior of consumers and suppliers. In my view, progress in these areas will create a unique research stream in marketing science that is well differentiated from its source disciplines such as statistics and economics.

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