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Foreword

Revisiting the Workshop on Quantitative Marketing and Structural Econometrics

Brett R. Gordon
Columbia Business School, New York, New York 10027, brgordon@columbia.edu

Raphael Thomadsen
UCLA Anderson School of Management, University of California, Los Angeles, Los Angeles, California 90095, raphael.thomadsen@anderson.ucla.edu

Eric T. Bradlow
Wharton School of the University of Pennsylvania, Philadelphia, Pennsylvania 19104, ebradlow@wharton.upenn.edu

Jean-Pierre Dubé
Booth School of Business, University of Chicago, Chicago, Illinois 60637, jdube@chicagobooth.edu

Richard Staelin
Fuqua School of Business, Duke University, Durham, North Carolina 27708, rstaelin@mail.duke.edu

This foreword and the subsequent four invited articles were commissioned by Eric T. Bradlow while Editor-in-Chief of *Marketing Science*. The foreword was written in four parts; each part covers a different aspect of the Workshop on Quantitative Marketing and Structural Econometrics. The workshop was cosponsored by Columbia Business School, Duke University, the University of California at Los Angeles, and the INFORMS Society for Marketing Science and was held at the Fuqua School of Business at Duke University in August 2010. The introductory section, written by Bradlow, covers why he commissioned these articles in the first place. In his section, Jean-Pierre Dubé discusses "going from good to great" in the structural econometrics area as applied to marketing problems. A section jointly written by Brett R. Gordon and Raphael Thomadsen (both co-organizers of the workshop) discusses the workshop itself and some important thoughts for those people doing "structural econometrics in the trenches." Finally, co-workshop organizer Richard Staelin's section provides some perspective on both the workshop and structural econometrics as they relate to analytical models and empirical work for quantitative marketing researchers.

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Eric T. Bradlow

During my last year as editor of *Marketing Science*, I was looking for opportunities to have a more lasting impact on the practice of academic marketing science than simply the papers that I handled or the tactical/structural changes that were made at the journal. Coming up with impactful plans is never simple, but one such idea came from the Workshop on Quantitative Marketing and Structural Econometrics. I insisted that many of our Wharton doctoral students attend, and they unanimously returned with "rave reviews." My only thought after they returned was, why do they get to have all the fun and learning?! Can't we find a way to share what was learned at this workshop with a broader audience—Ph.D. students, junior faculty, and senior faculty alike? It was that motivation that led to my contacting the conference organizers, asking them to reach out to some of the presenters at the workshop to see whether they would be willing to write invited pieces that would act as a "block of structural econometrics content" for marketing scholars that would "last in perpetuity."

My hope is that those reading the papers by

(i) Reiss on "what makes a model structural" and when it makes sense (and does not) to model things in this manner,

(ii) Mela on the data requirements (e.g., variation) needed for those thinking about employing structural methods,

(iii) Chintagunta and Nair, who write both on the economic foundations of structural models and on issues in model estimation, and

(iv) Ellickson and Misra, who write on static discrete games and how to estimate them, and who

provide a step-by-step guide to those learning these methods,
will see this as a must-read for all quantitatively oriented doctoral students. Finally, my deep thanks to Jean-Pierre Dubé, who acted as the Area Editor for all of these articles, and for my coauthors (and others) who acted as the reviewers.

Jean-Pierre Dubé

At least since the wide adoption of conjoint analysis by scholars and marketing practitioners, structural empirical research has played an important role in the quantitative marketing literature. Most structural work is geared toward the measurement of consumer preferences and the evaluation of marketing policies. For instance, a conjoint study might be conducted to estimate demand for new products and to simulate sales and profitability under various hypothetical launch strategies that vary such marketing decisions as prices and product configuration. Reiss (2011) provides a very clear definition of the structural approach to empirical research, which he compares and contrasts with descriptive and experimental approaches.

The workshops focused primarily on state-of-the-art methodologies for estimating structural models. But methodology alone does not characterize high-quality structural research. High-quality research in this area also distinguishes itself through the clarity and plausibility of the underlying inference scheme. Not surprisingly, each of the sessions at the structural symposium devoted at least some time to the topic of identification of causal effects. In practice, applied structural research should always be concerned about the extent to which estimated effects are inferred from data as opposed to untestable, ad hoc functional form assumptions. Some researchers downplay the importance of identification with statements such as "endogeneity is a passing fad" and "causality is overrated." This sentiment is merely a convenient way for researchers to avoid the complicated task of establishing the validity of their estimation strategy.

An important component of the structural researcher's inference scheme is the nonparametric identification of the underlying model. Granted, this is a theoretical exercise based on a hypothetical, infinite-sized data sample. But at this stage, the researcher establishes the importance of functional form assumptions and distributional assumptions for estimating the causal parameters of the model. The underlying concern is that different theoretical models, each with its own causal implications, may be consistent with the same data.

Many well-known identification problems plague some of the most popular, current areas of quantitative marketing research. For instance, research in the areas of social interactions and dynamics often pays lip service to identification without acknowledging the well-documented underlying econometric challenges (e.g., see Manski 1993, Moffitt 2001 for identification in models of social interactions, and see Rust 1994, Magnac and Thesmar 2002 for dynamic discrete choice models). Often, researchers inadvertently resolve these problems with strong parametric assumptions. Consider, for example, a test for forward-looking behavior in the context of discrete choice demand fit to revealed preference data. A naïve approach might consist of comparing the fit of a choice model with forward-looking behavior to one without. It is well known that without unusual exclusion restrictions, the consumer's preferences, discount factor, and beliefs are not separately identified nonparametrically. In this case, the test for forward-looking behavior is only identified with additional parametric restrictions.

As discussed in Mela (2011) and Reiss (2011), institutional knowledge and economic theory can often provide useful restrictions to assist with identification. When theory alone is insufficient, several other approaches can be used to generate the necessary variation in the data, or "instrument." A randomization that does not impact the underlying structural relationship of interest can serve as such an instrument. Consider the context of demand estimation discussed in Chintagunta and Nair (2011). The codetermination of sales and marketing variables in equilibrium potentially complicates the researcher's task of separately identifying the demand relationship from the supply side. Marketers have a long tradition of using conjoint studies that randomize the relevant marketing variables to identify the demand relationship.

Exclusion restrictions can also serve as instruments. The aggregate demand estimation literature using field data has a long tradition of relying on instrumental variables to resolve the endogeneity of marketing variables. These instruments consist of exogenous factors that shift marketing variables but that are excluded from the demand relationship. In the context of empirical games, Ellickson and Misra (2011) discuss how analogous exclusion restrictions across competing firms' profit functions can be used to identify competitive effects.

Brett R. Gordon and Raphael Thomadsen

The primary purpose of the workshop was to help students and faculty in marketing foster a deeper understanding of structural econometric techniques. The sessions drew on empirical work from a wide array of contexts and simultaneously addressed several philosophical issues underlying the application of structural models. We also wanted to provide students with an opportunity to meet others who share an interest in structural research.

The curriculum for the workshop, which can be found at http://faculty.fuqua.duke.edu/econometrics, sought to balance the breadth of topics fundamental to constructing structural marketing models with the depth of knowledge required to actually implement them. The topics included consumer-level choice models (covered by Pradeep Chintagunta and Wesley Hartmann), aggregate models of demand (Brett Gordon), single-agent dynamic models (Günter Hitsch), and empirical models of static games (Sanjog Misra). These topics form the core of modern structural methods. In all cases, the presenters offered examples of basic marketing problems that could be solved using the methods they presented.

The progression of topics was intuitive. Individual-level choice models have a long history in marketing and provide a solid foundation for understanding utility function estimation and numerous forms of consumer preference heterogeneity. Because individual-level data are not always available, the session on aggregate demand models covered the workhorse model of Berry (1995), including the newer estimation approach advocated by Dubé et al. (2010). Firms and consumers also make decisions that affect their future profits/utility. Hitsch showed how to construct and estimate dynamic models of decision making. His session both covered the general theory of Markov decision processes and went into the nitty-gritty details required to implement these models, including approximation techniques and using Mathematical Program with Equilibrium Constraints (MPEC) to estimate dynamic discrete choice models (e.g., Su and Judd 2010). Finally, firms rarely enjoy monopoly power, so they should consider the strategic response of competitors to their own actions. Misra discussed how to cast such situations as static empirical games and the various challenges involved in solving such games, such as necessary informational assumptions and multiple equilibria, and the implications of different solution techniques. In a different session, he addressed a key empirical issue: What does it mean for the parameters to be "identified?" Misra introduced this often illusory concept through a set of simple, intuitive examples. He also showed how to assess the extent to which the data, and not the assumed structure, drive a model's predictions.

An important goal of the workshop was not just to teach the "how" but also the "why" in working on structural models. These sessions also sought to clarify a frequently misunderstood point: structural models are not about fancy techniques or high-tech statistics. Complicating a model is not the same as adding structure. Rather, good structural models strive for parsimony and transparency.

This motivation led us to include several more philosophical sessions that touched on subjects that often receive too little attention. Peter Reiss's session offered a concise definition of what makes a model structural and contrasted this with both reduced-form and descriptive modes of analysis. In particular, a structural model builds on the theoretical primitives (e.g., a consumer's utility function) that are immutable as the economic environment changes. A "structural" model should stem from a theory that yields specific predictions about human behavior. Such a theory need not be restricted to standard rational economic models of decision making but could also incorporate psychological theories of consumer decision processes. For example, Goldfarb and Xiao (2011) estimate a structural entry game between managers who have limited levels of strategic ability. The key factor is that the theoretical primitives should simply be invariant to changes in the choice environment.

Sometimes the lines between structural and descriptive analysis are blurred. For example, in Misra's session on empirical games, he noted that firms' payoff functions are often assumed to follow an ad hoc, linear form with no theoretical underpinnings. In this case, the structure lies in the game itself and not in the functional form of the payoffs. These nuances demonstrate that no model is innately structural. Whether a model is structural or descriptive boils down to whether the behavior that is modeled is more primitive than the counterfactual analysis that is conducted.

All of this discussion presupposes two critical points: that the researcher has in mind a clear research question and appropriate data to tackle the problem. Hartmann's and Carl Mela's sessions, respectively, addressed these issues. Some questions are more appropriate or feasible to study using a structural model, and knowledge of the relevant institutional mechanisms is often critical. Hartmann's session discussed the process he uses to understand whether framing a problem from a structural perspective is the right approach. Structural analysis is most often used to conduct counterfactual analyses in which the researcher would like to understand how agents in a model would respond to an exogenous change in the environment. In his session, Mela did a great job walking students through the various strategies available to academics to acquire data, ranging from contact with former students to formal company engagements. Ultimately, he created a six-step process for data selection and procurement, which is presented in his article in this issue. The first step of this process involves identifying what data are needed to answer the research question; as Mela notes, a carefully designed identification strategy guides the data requirements for a project. We believe this guide will prove invaluable to both young students embarking on their careers, as well as providing thoughtful suggestions to more experienced researchers.

The success of the workshop could not have been possible without the support of several individuals and organizations. First, and foremost, we are grateful to all the presenters who generously donated their time and expertise: Pradeep Chintagunta, Wes Hartmann, Günter Hitsch, Carl Mela, Sanjog Misra, and Peter Reiss. We particularly appreciate Pradeep Chintagunta, Wes Hartmann, and Rick Staelin for serving on our organizing committee, where they provided valuable feedback throughout the planning process. We are also grateful to the INFORMS Society for Marketing Science, Columbia Business School, Duke's Fuqua School of Business, and the UCLA Anderson School of Management for their financial support. Finally, we are grateful to Eric Bradlow, Preyas Desai, and Jean-Pierre Dubé for making it possible to publish this collection of papers in *Marketing Science*.

Richard Staelin

When asked to comment briefly on how the material presented in the Workshop on Quantitative Marketing and Structural Econometrics fits in with analytic modeling and more traditional empirical modeling, my first thoughts went back to the debate on whether one should start with theory or empirical observations. This discussion is certainly not new. I remember reading a paper by Sonquist (1969) discussing a new methodology to uncover interesting relationships among observed variables. Sonquist's argument was that the discovered empirical observations (which were built on correlations) provided the researcher with interesting "stylized" facts or observations that could act as the impetus for developing new theories to explain these observations. Subsequently, Bass (1995) wrote a paper discussing how one might start with a theory and use it to generate further empirical work. He referred to the former approach as ETET (empirical-theoretical-empirical-theoretical) and the latter as TETE (theoretical-empirical-theoretical-empirical). Of course, either approach works; what is important is that the field (and the individual researcher) realizes that both approaches have value and are synergistic.

All this is relevant, since with the advent of structural modeling, one could argue that there is less of the stark dichotomy of reduced-form empirical modeling and analytic modeling. Thus, the former approach uses data to identify interesting patterns (correlations) to motivate or test new theory. In contrast, the latter starts with some stylized facts and uses a (parsimonious) set of assumptions to generate deep understanding of what might drive the outcome of the model. Structural modeling blends these two approaches by using the assumptions (and thus relationships) found in the analytic models and puts these relationships to data. As such, it allows one to test formally the assumed theory and identify possible misspecifications, thereby suggesting possible modifications. In this way it makes clear the connection between theory and empirics.

Taking this view calls into attention the strengths (and weaknesses) of all three approaches. Standard empirical modeling normally lacks the specificity needed to understand the underlying forces driving the observed relationships; this is the role of analytic modeling. However, analytic modeling, because it is not data driven, normally can only identify the directionality of these underlying forces and provides little opportunity to test the underlying assumptions. Here lies the potential advantage of structural modeling. It too starts with a series of underlying assumptions about the structure of the problem setting and uses these assumptions to obtain estimates to predict (with more precision) what might happen if the environment (but not the underlying structure) changes. It also provides a vehicle for testing the underlying assumptions. Of course, this potential advantage also has its potential problems because the predictions are highly dependent on the underlying theoretical assumptions needed for identification. Thus any misspecification of the true underlying model can greatly impact the estimation of the specific coefficients and thus the validity of any of the predictions. This is particularly true when these estimates are used to conduct a series of counterfactual experiments. Consequently, the challenge is to make sure that the underlying theory used is correct, because otherwise, the advantage of being able to specify an outcome with precision (versus direction) can become a liability.

Besides being able to identify elements of the structure via the application of theory, another key aspect of structural modeling that has garnered much recent attention is the issue of endogeneity. I find this interesting because this problem has been around at least as long as I have been involved in the field of marketing (and that is a long time). At one level the issue of unobserved (to the researcher) variables can be associated with almost every independent variable. One obvious way of addressing this problem is with instruments, although in practice these instruments are often hard to identify. Another possible approach would be to acknowledge that some marketing actions are strategic and thus are more likely to be "fixed" and therefore observable to both the researcher and the decision maker. If this is the case, perhaps one way of determining whether or not a particular action can be treated as being exogenous (and thus yield estimates that are not wrong) is to ask the manager about the information set being used. Such an approach may be less "scientific," but it recognizes that our field is applied and consequently can build on the fact that we are intimately connected with the profession.

The bottom line of this short note is that all three approaches should be seen as being synergist, because methodological and theoretical advances in one approach can enhance the progress in another. Thus, we are beginning to see some analytic models being solved using numerical techniques similar to those used in structural and/or empirical modeling. Likewise, new analytic models that address topics in areas where one lacks good data may find their way into the theory formulation used in structural modeling or reduced-form explorations once enough data are accumulated. In summary, all three approaches can and should be used to gain deeper insights into the complex world of marketing.

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