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Behavioral frontiers in choice modeling

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Abstract We review the discussion at a workshop whose goal was to achieve a better integration among behavioral, economic, and statistical approaches to choice modeling. The workshop explored how current approaches to the specification, estimation, and application of choice models might be improved to better capture the diversity of processes that are postulated to explain how consumers make choices. Some specific challenges include how to capture and parsimoniously describe heterogeneous mixes of heuristic choice rules, methods for building realistic models of choice, and nontraditional methods for estimating models. An agenda for important future work in these areas is also proposed.

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1 Introduction

We do not need academic studies to know that choice processes vary over people and situations. While one consumer may make choices by carefully trading off the pros and cons of options on different attributes (a compensatory rule), another may make that same decision by choosing that which is best on the most important attribute (a noncompensatory rule). Likewise, a consumer who undertakes an extensive search for information when buying a cell phone today may undertake little or no search when purchasing cell phones in the future, preferring just to choose the brand that was purchased before. Finally, tastes and decision processes may be conditioned by such situational factors as choice set size (whether determined exogenously or endogenously) and attribute variation.

This paper reports the findings of a workshop that sought to explore how current approaches to the specification, estimation, and application of choice models can be improved to better capture the diversity of processes that characterize how individuals make choices. The hope was that such an exploration would help facilitate a confluence of the economic, psychological, and statistical research streams that have come to dominate work in the field—streams that have had limited historical interaction.

We discuss our findings in two phases. We first describe the motivation for the workshop and summarize the major challenges that face researchers who attempt to bring greater behavioral realism to choice models. We then describe some attempts that have been made to meet these challenges and suggest an agenda for future research in the area.

2 Background: the competing ideologies

Three very different views of the ways individuals make choices underlie contemporary research in choice modeling. One view might be termed "economic,"

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taking a perspective that consumers make choices in ways that are consistent with random utility maximization. That is, consumers may be assumed to have well-developed preferences, defined narrowly over product attributes, and they choose alternatives with attribute bundles that offer the best tradeoff (e.g., Manski and McFadden 1981). Alternately, preferences in a utility-maximizing context may be defined more broadly to include other dimensions of the choice context, such as time–search costs, opportunities for postponement, etc.

A second view is more behavioral and psychological and argues that real choice processes may bear little resemblance to the rational processes that economists assume. In this view, if preferences even exist, they are lumpy and inaccurate; and choices result from unique heuristic rules associated with the external appearance of options in choice sets (e.g., Payne et al. 1993). Alternately, preferences are merely constructed at the time of choice, based on contextual factors, and any apparent preference for specific attributes merely reflects a derived demand resulting from preferences over much more proximal sources of satisfaction (Payne et al. 1999; Schwarz 1999).

A third view has rapidly gained adherents since the late 1980s, focusing primarily on statistical ways to model discrete outcomes (in this case, choices). Those who hold this view act as if they are ideologically neutral regarding preference and choice processes. That is, they tend to view choices simply as "data"; hence, any statistical choice model is considered "acceptable" if it has sufficient descriptive and predictive validity in a given application (e.g., Abe 1995; Ter Hofstede et al. 2002; Rossi et al. 2005; Kamakura and Wedel 2004). This view is consistent with a concern that preferences may be clear and well crystallized for the individual, but there may be a very noisy mapping from preferences to the observable attributes associated with the alternatives offered in any given choice set.

One might have expected convergence in these views over time, but this is rarely evident in the literature. For example, behavioral decision theorists have historically focused on demonstrations of how the assumptions of standard economic models (a) often fail in laboratory tests (e.g., context invariance) or (b) are driven by processes that are remote from those assumed in standard theory (e.g., Loewenstein 2001). Researchers in this area have traditionally displayed less interest in developing alternatives (i.e., to the structural economic models widely used in practical research) that might overcome these limitations[1]. Similarly, adherents to the economic view often dismiss behavioral research results by suggesting that laboratory settings exaggerate the sizes of the effects compared to what would be observed in real markets, or that the observed anomalies can be accommodated simply by specifying more general models and/or allowing for more latent factors in choice processes (e.g., Machina 1982; Train and Weeks 2005). Finally, those who hold the statistical view typically attempt to remain ideologically neutral in debates over theory by focusing on the development of methods that yield efficient statistical descriptions of choice data in a particular context with the fewest possible *a priori* assumptions about structure (e.g., Abe 1995; Ter Hofstede et al. 2002).

This neutral stance is attractive in principle because the number of possible statistical specifications will invariably exceed the information latent in the types of choice data normally available. (We elaborate on this point below). However, the

[1] For important exceptions, see Kivetz et al. (2004) and Tversky and Simonson (1993).

goal of neutrality with respect to the underlying theory is likely to be difficult to achieve in practice (i.e., in empirical implementation), as even the most general approaches require one to make at least a few strong assumptions about behavioral “data-generating” processes that underlie the choices that he or she wants to analyze.

3 So few choosers observed, so many possible decision rules

A fundamentally important question considered by the workshop is the degree to which it is possible to improve choice models through greater understanding of “real” decision processes. Indeed, it typically is scientifically impossible to identify which decision rule an individual uses to make choices.[2] For example, building on prior work, Batley and Daly (2006) show that generalized extreme value (GEV) and elimination-by-aspect (EBA) models can lead to the *same* choice probabilities, even though they rely on fundamentally different assumptions about the individual decision-making processes which underlie the choices. These choice models are therefore observationally equivalent, so one cannot know, simply from a set of observed choices, whether individuals use some process more like the compensatory decision rules of GEV models or one more like the elimination rules of EBA models. However, it is worth noting that economists (and other disciplines) are accustomed to conceding that all models are merely “as if” models, in the sense that the success of a model is judged only by its ability to predict observed behavior rather than any suggestion that subjects actually think that way in real choice situations (e.g., Zeger 1991). In some cases, of course, the relevant implications of choice analysis may turn out to be essentially invariant across a menu of alternative modeling strategies.

Similarly, most empirical choice experiments are associated with many observationally equivalent choice processes. Meyer and Louviere (2007) discuss how all observed choice patterns have associated “rules”, but unless one observes all possible sets of choices, many rules become observationally equivalent. For example, consider an experiment where one presents eight options to a person one at a time; the options being described by all combinations of three attributes, each with two levels (2^3). The person must “accept” or “reject” (yes or no) each option according to some criterion. This simple experiment has 256 possible outcomes (2^8), corresponding to all patterns of yes or no. If the preference directionality of each attribute level (i.e., whether the subject likes or dislikes more of each attribute) is known a priori and *all* individual preferences for these levels conform to this directionality, there are 128 possible yes or no patterns or choice outcomes; the rest are inconsistent in directionality.

To elaborate, note that one-at-a-time yes-or-no (1, 0) responses to a 2^3 experiment can be represented by a linear probability model (lpm). Each pattern has a unique lpm associated with it. Each lpm has seven parameters (a, b, c, ab, ac, bc, abc) that

[2] A good deal of the discussion in this Workshop concerned ideas which have not yet made their way into published papers. One of the most valuable aspects of this Workshop was the opportunity to hear some of the details of what our colleagues were just beginning to think about, rather than limiting the discussion to research which has already navigated the publication process. To afford some minimal protection to each individual’s proprietary rights to these ideas, we quote unpublished ideas and general expert intuition with attribution, wherever possible (even though this may go against the conventions observed in more standard journal articles).

can be estimated using orthogonal codes (i.e., all main effects levels are coded −1 or +1, and all interactions are cross products of coded main effects). For example, let the main effects signs be negative, such as bus fare, bus travel time, and bus service frequency. It should be clear that responses to this experiment could be generated by a wide variety of decision processes, each associated with its own unique parameter pattern. In this case, the rational patterns would be as follows (number of possible patterns in parentheses): "say yes" (a) to all (1); (b) to none (1); (c) if one particular attribute is good (3, lexicographic); (d) if two particular attributes are good (3); (e) if all attributes are good (1); (f) if one particular attribute is good or the other two attributes are both good (3); (g) any attribute is good (1). Additional numbers arise if the "rule" is additive in two particular attributes (3) or three particular attributes (1). Thus, there are a total of 18 possible rational patterns if there are sign restrictions. If signs on the attributes do not matter, there are many more possible patterns.

Now consider a larger experiment where a person chooses among four options, each described by four attributes with four levels (4^4). The total number of possible choice sets is 4,294,967,296 (256^4), of which a small number can be dismissed as (a) all choice options are identical and (b) one option dominates the rest or is dominated by one or more others. Even with these restrictions, the number of possible nondominant sets is so large that it is unlikely that anyone would be able to design and implement such an experiment, much less find any individuals willing to participate. We note that by choice experiment standards, this is a *very* small problem. Yet, even this small problem leads to $4^{(\text{number of choice sets})}$ possible choice response patterns. A typical choice experiment for this case in a survey might involve 16 or 32 choice sets, which leads to 4^{16} or 4^{32} associated possible choice patterns (4,294,967,296 and 1.84467×10^{19} patterns, respectively). Thus, millions (literally) of choice patterns are observationally equivalent in this small experiment. Each pattern has an associated decision rule, so it is impossible for researchers to uniquely identify the "real decision processes" from choice experiments, including small experiments.

This problem can be solved, of course, if one can make the assumption that only a small number of decision rules are psychologically plausible, something that would greatly pare down the number of possible parameter patterns. For example, Gilbride and Allenby (2004) developed an approach to analysis that assumes that when consumers make choices they use one of three types of decision rules: compensatory, disjunctive, or conjunctive. Under that structural assumption, they are then able to recover the mix of these rules that is being used by consumers in a population. The problem with this (and similar) approaches, of course, is that there is no means of internally verifying the validity of the basic structural assumption. If, in fact, consumer choice rules do not neatly fall into simple "conjunctive" or "disjunctive" categories (as argued by Payne et al. 1999), then the behavioral insights that can be provided by such methods would be rather limited.

4 Many people observed, but only a few decision rules

How may "psychologically plausible" choice rules are there? While the number is almost certainly greater than the simple conjunctive, disjunctive, and compensatory dichotomy popularized in the literature, it is also likely to be far less than the complete enumeration of choice sets as in the example above For example, we discussed work in progress with Jordan Louviere, Richard Carson, Ian Bateman, and Paul Wang that involves a sample of almost 900 people in East Anglia, UK. These subjects were asked to evaluate possible new water supply scenarios relative to their present water supply. Each person was shown eight scenarios described by the number of days where the smell or color of the water would be "better" than the current situation and a price they must pay to realize each specified improvement. Each attribute in the target experiment has two levels, so there are eight supply description scenarios that individuals could choose to accept or reject, where rejection means that they keep their present water supply.

The researchers found that six simple deterministic rules account for 96% of the choices made by the sample. An example of such a rule was, "say yes if poor color days equals five and poor smell days equals five; otherwise, say no." Approximately ten more rules accounted for virtually all other choices in the sample. Only 12 people seemed inconsistent in their choices or used a stochastic process. The design was a full factorial, so it was possible to: (a) identify all possible rules, (b) exactly determine each person's rule, and (c) discover how many rules will account for most of the choices. While it is uncertain the degree to which this pattern of rule heterogeneity generalizes to other choice tasks, it nevertheless shows that heterogeneity in choice rules may be very important in any explanation of differences in observed choices across individuals. In contrast, much work over the last decade has focused on parameter heterogeneity, conditional on a single assumed choice rule.

5 So many possible processes, so many ways to get there

Our session reviewed recent work where theoretical considerations led to better model specifications. We discussed several ways that psychological insights can be or have been used to formulate better choice models. We previously noted that it is very difficult to know exactly what decision rule an individual actually uses. Meyer and Louviere (2007) discussed how trial-and-error learning can lead to decision rules that appear to be compensatory, when the real process results from a person learning how to match patterns over successive trials. Such a learning process involves the use of a pattern-matching process to make forecasts about how similar a new option is to an option (with known features) seen earlier. Decisions get better over time as individuals compile a set of examples in memory that "work"; hence, choices behave "as if" a compensatory decision rule underlies them even if the actual choices involve only pattern matching based on previous events. How well a pattern-matching learning process like this mimics a compensatory decision rule will depend on the sample of options in the choice scenarios from which a person learns. Samples that cover a relatively large part of the multiattribute space lead to compensatory-looking behavior, but samples limited to one area of attribute space, or that otherwise have the ranges of their attribute levels systematically restricted, will lead to behaviors that look noncompensatory.

Meyer and Louviere (2007) also noted that most choice modelers assume that every person is an "error variance clone," such that variability in choices is constant within and between individuals. They discuss considerable evidence that this is false and, when it is false, that this can lead not only to bias in choice model parameter estimates but also to mistakes like concluding that individuals with the same decision rule but different choice variability have different preferences (see also Louviere and Eagle 2006; Cameron et al. 2002). In this vein, we discussed work under way by Keane, Louviere, Fiebig, and Wasi to develop a more general logistic model that nests many other models in the literature. Called "Generalized Logit," or G-Logit, this model can distinguish between variance (i.e., scale) heterogeneity and preference heterogeneity. Results of tests on eight datasets show that scale heterogeneity plays a potentially larger role than previously believed. The latter result is consistent with results reported by Meyer and Louviere (2007) showing that scale can account for between 0% and 50% of variability in individual-level model estimates, with an average of around 16%.

The workshop then discussed the issue of choice involving subsets of similar alternatives, a long-standing problem that has intrigued both economists (e.g., McFadden 1974a, b) and behavioral researchers (e.g., Tversky 1972). Steenburgh (2007) showed that many discrete choice models that purport to "solve" the independence from irrelevant alternatives (IIA) problem (including GEV and covariance probit models) do not necessarily address the broader concerns that Debreu (1960) illustrated with the "Beethoven–Debussy" example.[3] These models possess another property, Invariant Proportion of Substitution (IPS), which implies that the proportion of demand drawn from a given competing alternative is the same no matter which attribute is improved. This is counterintuitive because, all else equal, we would expect preferences for a competing alternative to suffer more if the improved good becomes more similar to it. The IPS property arises because the unobserved component of utility is independent of the observed attributes of the different alternatives in these models. We reviewed an example that shows that models that allow for taste heterogeneity do not necessarily address Debreu's concerns. Models that could prove useful in addressing concerns raised by IPS include those with error components that depend on observed attributes, and the Universal (or "mother") Logit model (McFadden 1984).

In addition to psychological insights, choice models may be improved by further in-depth examination of behavioral implications from microeconomic theory that recognize the importance of budget constraints in determining choice behavior. Many published choice models are based on conditional indirect utility functions that are sometimes selected based on general consistency with an underlying constrained (direct) utility maximization problem. The selected specification is then applied to practical empirical analyses with only a tangential connection to the underlying theory. We discussed examples related to "whether, which, and how much to buy" information in scanner panel data, which showed that specifications derived from the maximization of direct utility yield functional forms with parameters and error structures that maintain clear and useful behavioral inerpretations. In particular, the potentially important role of the expenditure budget (critical in economic models but frequently ignored in marketing applications) was highlighted.

[3] Some progress has also been made recently in addressing this concern via EBA models (see Batsell et al. 2003).

6 So many things to choose, so little satisfaction with what is chosen

Recently, researchers have begun to study the impact of choice set sizes on choice and on satisfaction with choices. Normatively, of course, a utility-maximizing consumer would always be better off given the opportunity to make a choice from a larger choice set as opposed to a smaller one, but there is growing evidence that this may not always be the case. For example, Iyengar and Lepper (2000) and Schwartz et al. (2002) illustrate cases where larger choice sets lead to fewer purchases and less satisfaction with choices made. Yet, the "choice set overload" phenomenon is hardly universal; while some choice set structures indeed appear to produce consumer frustration and a desire to defer choice, others lead to high levels of satisfaction and a desire to accelerate choice (e.g., Meyer 1997).

To reconcile such differences, Swait and Adamowicz (2001) suggested that the attractiveness of a choice set as perceived by consumers might correspond to the degree to which alternatives are similar in utility terms or lie upon an isoutility curve. Formally, they define the "quality" of a choice set X in terms of the entropy measure

$$H(X) = H(\pi_X) = -\sum_{j=1}^{J} \pi(x_j)\log(\pi(x_j)),$$

where $\pi(x_j)$ is the probability that alternative j with attributes x_j is chosen. Thus, entropy is at a maximum when all of the alternatives are equally likely to be chosen. If the number of equally likely alternatives increases, entropy increases at all levels of choice probability.

Will consumers prefer higher- or lower-entropy choice sets? Swait and Adamowicz (2001) hypothesized that this depends on the degree to which consumers tend to be utility maximizers or satisficers when making choices. Utility maximizers who feel it important to know that they have chosen the best possible option should prefer heavily skewed or lower-entropy choice sets that contain a clearly "best option". On the other hand, satisficers who are looking merely to quickly identify an acceptable option should prefer higher-entropy sets where all options are equally plausible. In a recent experimental study, Johnson et al. (2007) found support for this idea, showing that when consumers are allowed to construct their own choice sets their structure corresponds to such a predicted pattern. Additionally, Swait and Adamowicz (2001) show that the structure of choice sets also can affect error variances in choice models and preferences.

7 So many attributes to consider, so few theoretically sound ways to do it

Given the inherent difficulties noted earlier for the task of model selection based on choice outcomes alone, it is important to identify and/or develop theoretically motivated ways to select appropriate models or at least to select key model components like the array of included attributes. Ideally, such methods would be used to inform model selection *before* designing experiments or estimating models. Historically, qualitative research methods have been used to identify the relevant attributes used to describe alternatives in choice models and experiments.

For example, in-depth interviews and focus groups are commonly used to study consumer preferences (Griffin and Hauser 1993), with laddering techniques used to study consumers' cognitive value structures (Reynolds and Gutman 1988).

More highly structured approaches also have been used. In particular, the repertory grid approach often is used to identify attributes that individuals rely on in a given decision task (Louviere 1988; Kelly 1995; Tan and Hunter 2002). Association pattern techniques impose further structure, with individuals being asked to select the most relevant attributes, as well as the benefits these attributes provide, from a list of options predefined by researchers (Ter Hofstede et al. 1998). These techniques also can be used to study differences in choice model attributes, attribute relationships, and tradeoffs between groups (Ter Hofstede et al. 1998) or usage situations (Wendel and Dellaert 2005).

Recent advances have occurred in three main areas. First, existing approaches have been adapted to online data collection to take advantage of quality and efficiency features of the Web (Dahan and Hauser 2002). Second, growing evidence suggests that tailored incentive schemes help individuals provide more insights into decision attributes and preferences that also are more truthful. For example, Prelec (2004) develops an elegant scoring method to elicit truthful subjective information in case an objective truth cannot be identified. And third, some authors propose giving more attention to how mental representations of complex decision problems are constructed (e.g., Loewenstein 2001), which has led to ways of measuring such representations, including differences between users and across choice situations (Arentze et al. 2008). These three areas can potentially lead to better, more informed, ways to select model attributes and attribute relationships that determine individuals' key tradeoffs in different situations prior to data collection and model estimation.

Another advance in representing complex decisions is the Price Consideration Model. In many markets (e.g., cell phones), consumers face literally hundreds of choice options, so it is implausible that they would consider all of the attributes of all options before making a choice. Yet, many current choice models make this assumption.[4] For example, consider a nested logit model applied to cell phone choice. At the top level of the "correlation structure diagram," consumers decide on a brand (e.g., Nokia vs. Motorola) and at the next level they consider all the models for the chosen brand. Nested logit is widely misinterpreted as a sequential choice model, but in fact, in order to decide whether to go down the Motorola or Nokia branch of the tree, consumers must evaluate *all* types of phones offered by each brand. From a behavioral point of view, such complicated backwards recursion seems impossible.

The model of Ching et al. (2007) breaks this backward induction process. Consumers are assumed to make choices at the top level of the tree without looking forward to values at the next levels. For example, they might choose between Nokia and Motorola brands based on prior experience, word of mouth, advertising, etc., but they do this *prior* to looking at the attributes of the many specific phones currently offered by each brand. This is called a "price consideration model," or more generally an "attribute consideration model," because consumers use *prior* information to decide whether to consider attributes of offerings from a specific

[4] This is true of conventional conditional logit-type models, although lexicographic and EBA-type models, of course, depart from this assumption.

brand, whereas conventional choice models assume that they consider the attributes of *all* offerings. Ching et al. (2007) show that this model fits choice data much better than conventional and nested multinomial logit for both categories studied.

8 So many ways people may differ, so few models to deal with it

From the perspective of measuring preferences with random utility theory (RUT), interactions of context (generally thought to include at least choice set size and structure, as well as attribute configurations) and tastes raises serious issues of potential confounds between these different constructs. Specifically, RUT-based models commonly identify only a product of scale and tastes (in linear-in-parameters models) as noted by Louviere et al. (2000) and Swait (2007). Econometric probit and logit-based choice models acknowledge that utility parameters are "identifiable only up to a scale factor" (i.e., only in ratio to the error dispersion parameter), which is the same idea. Consequently, taste and scale heterogeneity may be confounded in real choice settings. Unless one controls for scale heterogeneity (i.e., heteroscedasticity in the error distribution), it may manifest itself in the estimated dispersion parameters of the individual random taste parameter distributions when a random parameter model is estimated. In cases where tastes *per se* are of direct or indirect interest, decomposing scale and taste heterogeneity should be a major concern (e.g., in product design and segmentation in marketing and in welfare estimation in applied economics). Research has shown that scale heterogeneity can be a function of the configuration of attributes in the choice set (e.g., Dellaert et al. 1999 for price ranges in choice experiments), numbers of attributes (DeShazo and Fermo 2002), and exogenous characteristics. For example, Swait and Adamowicz (2001) parameterized scale as a function of choice set entropy, simultaneously capturing the impact of choice set size and the attribute mix on scale differences. We noted that the range of factors that can affect scale is not only large but can be frustratingly application specific; yet, this should not deter us from considering practical ways to control for scale heterogeneity (i.e., heteroscedasticity) in choice models.

More generally, the field has focused recently on preference heterogeneity to the virtual exclusion of all other forms of heterogeneity, and mostly on random, rather than both random and systematic, heterogeneity. For example, individual preferences and choices may differ due to differences in decision rules (utility specifications), choice processes, contexts, culture, geography, time, and many more. The workshop identified and discussed a disturbing trend wherein a growing number of researchers seem to view the "appropriateness" and value of research on the basis of current research fashions, instead of scientific objectivity. Nowhere is this more prevalent than for research into forms of heterogeneity and "appropriate" ways to estimate models that allow for different forms. Not only are such debates unhelpful in advancing the field, they can effectively stifle innovation, new insights, and new directions for research.

At a minimum, we would like to see the field focus more attention on other forms of heterogeneity instead of the current fixation on what we term "residual taste heterogeneity." Examples are scale heterogeneity and new and different forms of heterogeneity, such as heterogeneity in the attention individuals pay to choice options and attributes, heterogeneity in the rules that underlie choices, and combinations of these forms of heterogeneity (e.g., Gilbride and Allenby 2004). For example, we discussed work in progress by Cameron, DeShazo, and Burghart concerning ways in which seemingly innocuous decisions by researchers about the designs of choice sets can impact inferences about preferences. Their work relies on a theoretical model wherein consumers optimize their allocation of attention to different attributes (and alternatives), where there are parallels to experimental research involving bounded rationality (e.g., Gabaix et al. 2006). Louviere and others are studying bias in choice models and distributions of tastes associated with common designs used to study choice processes characterized by different underlying deterministic or stochastic decision rules.

Finally, we note that the previously discussed G-logit model allows explicit estimation and tests for differences due to heterogeneity in tastes, heterogeneity in scale (heteroscedasticity), and differences due to a combination of both types of heterogeneity. Although this work is at an early stage, initial results suggest that there is more scale heterogeneity associated with more complex and significant decisions like decisions about medical treatments and less scale heterogeneity associated with common decisions like ordering pizzas.

9 Future work

This workshop aimed to explore research gains that might be achieved by fusing some of the major economic, psychological, and statistical ideologies that dominate the study of choice. Although participants came from a variety of backgrounds, they shared the common view that such fusion is essential if we are to address the many unresolved problems that confront both basic theoretical research in decision making and applied public and private sector applications.

The workshop reached mixed conclusions about achievements to date and future prospects. On the one hand, encouraging advances have been made in developing analytic tools and theoretical insights that allow accurate “snapshot” models of choice. For example, behavioral research has played a useful role in informing modelers of the need to develop representations that assume that consumers attend only to limited aspects of decision environments when making choices (implied by noncompensatory choice rules), and modelers, for their part, have returned the favor by developing improved statistical tools that try to capture such processes.

One of the challenges the workshop addressed that suggests promising opportunities for future research is the need to develop new theoretical insights into how contextual determinants of consumer choice processes combine with individual differences in choice. In particular, such work could integrate research on choice and choice process heterogeneity to provide a better understanding of the key situational determinants of consumer decision making. Theory on behavioral variation in choice is crucial not only to deepen our understanding of consumer choices but to allow researchers to distinguish between statistical choice models that may have (largely) identical fit characteristics in a current market context but may not extrapolate equally well to other (perhaps forecasted) market contexts. This is especially relevant when only limited data are available, for example, due to limited variation in market supply and therefore in prices or in the range of available alternatives in a given dataset. This research focus is also relevant for managers and policy makers as technology-based interfaces now let individuals interact with organizations in increasingly varied types of usage situations (e.g., home over the Internet, with mobile devices on the road, or traditional face-to-face interactions), making it harder for firms to anticipate an individual's decision-making context in any given interaction. Research in this area should begin to be available soon, and while true fusion has yet to be realized, we expect significant progress on such problems in the near future.

On the other hand, the workshop was less encouraged by the prospects for collaborative progress toward attaining what many see as the Holy Grail of choice research—namely, truly dynamic models of markets that do not suffer from the Lucas (1976) critique.[5] Workshop participants believe that a fusion of research skills could have the greatest payoff here, so it is surprising how few attempts have been made at cross-disciplinary work in this area.

As an example, some of the recent empirical literature in industrial economics (within the disciplines of economics and marketing) has focused on the estimation of dynamic structural models. For instance, some of these models try to capture, endogenously, how consumer responses to price variation adapt to changes in sellers' pricing policies (and vice versa). However, innovations in the specification of such models seem to have been held back by a paucity of behavioral guidance on issues such as (a) how consumers and firms actually solve dynamic decision problems and (b) how quickly the response strategies of consumers and firms will allow them to adapt to changing circumstances (see, e.g., Houser et al. 2004). With little guidance concerning the right assumptions about dynamic decision behavior, economic modelers have tended to adopt a set of placeholder assumptions that they know are likely to be incorrect (such as the assumption that both consumers and firms make strategic decisions in an optimal manner). The resulting lack of face validity means that much current work in dynamic structural modeling has had less impact on empirical practice than it would have appeared to promise.

That said, it is important to emphasize the point that the task of building behaviorally realistic structural models is not easy, partly because psychologists have paid only limited attention to the choice processes we seek to model. For example, one thing that makes economic modeling difficult is that there is no simple answer to the question, "is people's behavior dynamically optimal?" That is, in any real market or other choice context, one is likely to see a mix of degrees of optimality, and this is not helpful in formulations based on assumptions of process homogeneity. Unfortunately, we are not aware of any existing behavioral research, akin to work on static decision rules like noncompensatory strategies, that can provide *a priori* guidance about the kinds of dynamic decision rules likely to be used in actual or hypothetical markets. Moreover, even if such a taxonomy of rules could be developed, one simply faces another endogeneity problem of the Lucas critique variety—the types of rules that people use are likely to be adapted dynamically in response to changes in market environments controlled by sellers. Thus, while the

[5] The "Lucas critique" warns against the use of econometrically estimated models to evaluate policy proposals when the behavior of individuals is conditional on the proposed policy. This advice is based upon the argument that changes in the exogenous variables in a structural model can precipitate changes in the parameters of that model, a form of dependence that is assumed away in most econometric specifications.

task of building behaviorally realistic dynamic structural choice models is daunting, we do not see it as intractable. However, it will require serious and sustained research collaborations between economists, psychologists, and statisticians like those discussed, explored, and proposed in this workshop.

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