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Dynamic Influences on Individual Choice Behavior

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Abstract

Research examining the process of individual decision making over time is briefly reviewed. We focus on two major areas of work in choice dynamics: research that has examined how current choices are influenced by the history of previous choices, and newer work examining how choices may be made to exploit expectations about options available in the future. A central theme of the survey is that if a general understanding of choice dynamics is to emerge, it will come through the development of boundedly-rational models of dynamic problem solving that lie on the interface between economics and psychology.

Key words: choice models, dynamic decision making, learning, strategic decision making

Consumer choice is inherently a dynamic process. Whether we are observing routine purchases of brands at supermarkets or once-in-a-life choices of housing, choices made in the present implicitly reflect what has been learned from the past and, often, expectations about the future. Yet while the importance of understanding the nature of dynamic influences on choice is widely recognized, our knowledge of how choice evolves over time remains highly fragmented. The view of decision making that pervades most of the literature on choice theory remains largely static, quite adept at describing the momentary relationships that exist between preferences and actions, but less able to describe the dynamics that gave rise to these relationships.

The purpose of this paper is to review research that has attempted to broaden our understanding of dynamics in individual choice behavior. Because the literature that touches on this topic is large, our review is selective, highlighting work on two general problem areas: how current choices are influenced by the history of past choices (learning and state dependence), and forward dynamics, or how current choices may be influenced by expectations about choices to be made in the future. We thus omit such topics as time preferences in decision making (such as subjective discounting), and recent technical advances in statistical analyses of discrete panel data—a topic its own right.

In Table 1 we portray the approaches to modeling choice dynamics that we explore in this review. The table organizes work in terms of two descriptive dimensions: whether the analyst adopts a structural versus reduced-form approach to model building, and whether choices on each occasion involve strategic foresight of choices likely to be made on later occasions. Together, the dimensions portray a central tension that has marked the evolution of the literature on choice dynamics over the years: that between an emphasis on parsimony and analytic tractability on one hand, and psychological validity and explanatory detail on the other. Hence, at one extreme are reduced-form models where the analysts' goal is to obtain a simple statistical description of time-dependencies in choice. At the other extreme are recent models of individual dynamic utility maximization that provide such explanation while conceding parsimony.

Table 1. Taxonomy of research on decision dynamics

	Model Basis	
Assumed Decision Horizon of Consumers	Reduced-Form	Structural
Myopic; current choices are influenced only by the effect of previous choices	*Models of State-Dependence*	*Models of Expected-Utility Maximization, Behavioral Learning Models*
	Guadagni and Little (1983); Papatla and Krishnamurthi (1996); Massy, et al. (1970)	Meyer and Sathi (1981); Roberts and Urban (1988); Gilboa and Pazgal (1995)
Global; current choices are influenced by past choices as well as expectations of the future	*Reduced-Form Models Incorporating Expectations*	*Dynamic Programming Models, Models of Taste Manipulation*
	Bridges et al. (1995); Kalyanaram and Winer (1995)	Erdem and Keane (1996); Gonul and Srinivasan (1996); Bodner and Prelec (1996)

Dynamics without foresight: How purchase histories affect choice and preference

Since the first analyses of systematic analyses of consumer panel data in the early 1960's, it has been widely observed that the probability that a household will choose a particular brand or product on a choice occasion is conditioned by the choice made on the previous occasion (e.g., Kuehn 1962). These early observations spawned the development of a large contemporary literature of statistical models for discrete panel-data analysis, all offering approaches to representing temporal dependencies in choice probabilities (e.g., Guadagni and Little 1983; Heckman 1981; Keane 1996; Massy, Montgomery, and Morrison 1970; Papatla and Krishnamurthi 1992). Although this literature is diverse, most formulations follow a common approach: household brand-choices are initially represented by a static or cross-sectional random-utility model (such as the multinomial logit), and dynamics are then introduced by allowing preferences to be state-dependent, such as evolving as a Markov process (e.g., Guadagni and Little 1983).

Such formulations provide a parsimonious means of describing choice behavior over time in markets where dynamic influences are likely to be stable. For example, they provide a useful characterization of a tendency among consumers to seek variety in choice (e.g., Givon 1984), or be subject to spells of habituation or brand loyalty (e.g., Jeuland 1979). In both of these cases, while choice probabilities are vary over time, the form of state dependence itself is stationary.

Current representations have difficulty, however, when applied to *turbulent* markets, where the set of options—and consumers' beliefs about them—is changing over time, and learning is a driving force underlying changes in choice probabilities. Although, in principle, learning can also be statistically modeled as a form of state dependence (e.g., Kuehn 1962), in the absence of a formal characterization of what is driving learning such representations can be used for forecasting only to the degree that past trends can be directly extrapolated to the future—something that few analysts feel comfortable with.

The literature on attempts to explicitly model learning and information-gathering in discrete-choice models is, unfortunately, small. Probably the best-developed attempts are those that draw from statistical decision theory, modeling learning over time in markets as a sequence of rational decisions under uncertainty (e.g., Meyer and Sathi 1985; Roberts and Urban 1988; Erdem and Keane 1996). In these consumers are assumed to view the relative attractiveness of each option in a market as a distribution of possible values. Consumers are then assumed to act as intuitive utility theorists, on each occasion choosing the option that has the highest expected utility, and then using Bayes' rule to update prior beliefs about the utility distributions of each option.

These models provide a detailed behavioral account of why choice probabilities may follow different evolutionary paths during periods of product learning. In classic models of product-sales growth—such as diffusion or linear learning models—changes in behavior over time evolve as a largely deterministic process, with sales assumed to evolve in terms of a limited family of growth functions. When variations in the empirical parameters of these functions are modeled, rates of growth are expressed as an *ad-hoc* function of exogenous variables, such as market prices or comparative rates of advertising (e.g., Horsky and Simon 1983). In contrast, dynamic decision-theoretic models make no *a* *priori* assumptions about the likely functional form of the sales growth curve. Rather, different empirical sales patterns reflect the pattern of product sampling undertaken by consumers over time. These individual decisions, in turn, are modeled as a function of the prior expectations consumers hold for products, the rate at which they learn, and changes in the attributes of products induced by sellers.

Problems with EU models: case-based learning

Although decision-theoretic models provide a useful tool for explaining learning patterns in choice data, they nevertheless hold limitations. The first is pragmatic: the models require measures of beliefs about such things as distribution of utility values, the experienced utility after a trial, and the amount that is actually learned, something that goes beyond the domain of normally-available panel data. Another concern is more philosophic: while the idea that consumers make decisions as intuitive statisticians may be defensible as a useful *as if* assumption, it is dubious that consumers actually make decisions under uncertainty, and learn from the outcome of decisions. It is unlikely, for example, that consumers explicitly think of the uncertainty associated with new product options in terms of probability distributions, and there is extensive evidence that casts doubt on the ability of Bayes' rule to serve as a description of how individuals revise beliefs about uncertain events in light of data (e.g., Gigerenzer and Hoffrage 1995; Hutchinson and Alba 1996).

An emerging approach to modeling repeated choice under uncertainty which has the potential of offering a more compelling behavioral account of choice over time is *Case-Based Decision Theory* (CBDT). CBDT was originally formulated by Gilboa and Schmeidler (1994) as a theory of decision making under uncertainty for decision problems where the normative procedure of enumerating and assessing the likelihood of all possible future "states of the world" is implausible, either as a description of the way people make decisions or as a prescription for rational decision making. The key premise is that when considering different courses of action, the decision maker looks back and evaluates how each possible action has performed in "similar" previous decision situations. For example, when considering whether to try a new brand of toothpaste by a particular manufacturer, the decision maker will recall previous episodes of trial that hold parallels (for example, trials of other tooth pastes, or trials of other products by that manufacturer), and base choice on what was learned from those experiences.

In the formalization of Gilboa and Schmeidler (1995), the value $U(a)$ assigned to a possible act 'a' in decision problem 'p' is modeled as a weighted sum of the utilities $u\,(a, q)$ that the action has yielded in past problems 'q':

$$U(a) = \sum_q s(p, q)u(a, q)$$

The weights $s(p, q)$ define the similarity of past choice situations to the current one. The same formal model may be reinterpreted so that the memory of past choices is regarded not just a source of information but as something that determines utility directly (Gilboa and Schmeidler 1993). In other words, the desirability of an act depends intrinsically on previous actions. Under this interpretation, the function u would be the derivative of the memory-dependent aggregate utility U with respect to the number of times an act is chosen. If u is negative, the desirability of an act goes down as it is chosen more often. This would model boredom-averse or variety-seeking decision makers. Conversely, if u is positive, an act becomes more desirable the more it has been experienced, which would model habit-forming consumers.

Gilboa and Pazgal (1996) translate this into a model of brand-switching, where a consumer's impression of each brand is based on her memory of past consumption of this brand. In the cardinal version of the model, the consumer remembers a cumulative utility index per brand, which is updated by a random, brand-specific bit of "instantaneous utility" whenever the brand is consumed. In the ordinal version of the model, the consumer's memory captures only the ordering of the available brands. The currently top ranked brand is chosen and consumed, after which it may change rank. Both versions of the model assume that the consumer is sometimes "dormant," choosing the same brand out of inertia. Empirical tests of the model on panel scanner data confirm the existence of both "memory effects" and "inertia effects."

At this point, CBDT is both a family of existing dynamic models as well a general language for developing other "learning-from-experience" models that do not impute explicit probabilistic reasoning to the decision maker. If it has a limitation, it is thus that it might be seen as going *too far* in presuming that consumer choices are entirely comprised of "bottom-up" reasoning skills. In particular, there may well be times when consumer choice under uncertainty will, in fact, involve explicit considerations of likelihoods and expectancies as are presumed in the Bayesian models above. An interesting—and challenging—direction for future work might be thus to explore the possibility of achieving a fusion between these two streams.

Forward planning and dynamic utility maximization

It is important to stress that even the behaviorally-grounded models of learning described above are "dynamic" only in the limited sense that they incorporate time-varying variables in an otherwise static choice model. In contrast, a *structurally dynamic* model would be one that recognizes temporal dependencies in the utility-maximization process itself. For example, given that a learning process exists or that consumers seek variety, a dynamic-structural model would incorporate an anticipation of this. Hence, a dynamic utility-maximizer might prefer to choose an unfamiliar option over a familiar favorite because the choice may provide information that will benefit later choices, or allow the more preferred option to be chosen later when consumption would convey greater utility (e.g., Lowenstein and Prelec 1993).

There is ample evidence that beliefs about the future routinely arise in the course of consumer choices. For example, there is a large literature demonstrating "reference price" effects in choice, where it is shown that consumers are quite sensitive in purchase decisions to beliefs about the "normal" price for a good, revealing a tendency to accelerate purchases if the momentary price is below these expectations, and delay if it is above (e.g., Kalyanaram and Winer 1995). A perhaps even more striking example is found in recent work by Mela, Gupta, and Lehmann (1996), who report market-level evidence that chances in pricing policies induce changes in how consumers respond to price. One explanation for this finding is that consumers' decisions about whether to purchase at a given price may be influenced by beliefs about prices likely to arise in the future. The more common price promotions become, for example, the lower the rational sensitivity to promotions (Assuncao and Meyer 1993).

An implication of these findings is that if consumers engage in such forward-planning, reduced-form models that do not take into account expectations will produce parameters that cannot be used for policy evaluation (*as if* analysis). In particular, because static model parameters are a function of expectations of policy, any change in policy will change the parameters of the model—hence, current parameters may be of little use in evaluating the impact of hypothetical policy changes (Lucas 1976). Correcting this problem is not simply a matter of adding additional explanatory variables—such as "expected price"—to static formulations—one needs a formulation where parameters are formally endogenous to the policy system they are responding to.

Exactly how one should specify dynamic structural models that capture such endogeneities stands as one of the major challenges to current work in choice modeling, and we are just now beginning to appreciate both its importance and, unfortunately, its difficulty. The central obstacle to work in this area is that we currently know much less than we would like about how consumers plan, thus have few behavioral guidelines for suggesting dynamic specifications. In the absence of such knowledge, many analysts assumed that consumers solve dynamic choice problems as optimal decision makers, following the principles of stochastic-dynamic programming. Erdem and Keane (1996), for example, have estimated a dynamic-structural model that assumes that consumers make brand choices by explicitly considering the normative value of the information they are likely to gain through product trial. Likewise, Gonul and Srinivasan (1996) have estimated a dynamic-structural model for diaper purchases that assumes parents optimally plan over likely future availabilities of coupons when making purchase-volume decisions.

Are consumers intuitive dynamic planners?

How reasonable are assumptions of optimality in dynamic-structural models? On one hand, because published applications have reported that such models tend to provide a reasonable description of actual choice behavior (compared to best-fitting reduced-form models), optimality is not horrible as an as-if assumption, and might provide a reasonable starting place for empirical analysis. On the other hand, it is unclear whether the observed *lack-of fit* should be interpreted as alarming evidence of process misspecification, or simple random measurement error in an otherwise well-specified as-if model.

There has recently been increased interest in work that conducts detailed laboratory tests of the descriptive validity of decision-theoretic models of dynamic choice. This research, reviewed in greater detail by Hutchinson and Meyer (1994), tends to follow a common formula. The researcher begins by observing how subjects make decisions in a controlled laboratory task for which dynamic decision theory makes a specific prediction about behavior. For example, such a task might be to make a series of purchases of a hypothetical good under uncertainty about future prices (e.g., Krishna 1994b), or a sequence of decisions about whether to replace a durable good under uncertainty about future rates of deterioration (e.g., Cripps and Meyer 1994). Analyses then focus on the degree to which actual behavior conforms to the predictions of optimal theory. The general conclusion is that while optimal models can indeed often serve as reasonable first approximations to actual behavior, they also display errors that are not unbiased (e.g., Huber and Feinberg 1996). Specifically, subjects' inabilities to intuitively perform the mathematics of sequential analysis (e.g. dynamic programming and Bayes' Theorem) lead to problem simplification and editing processes that, in turn, often produce systematic deviations from optimality.

To illustrate, one consistent finding that has emerged from laboratory tests of optimal purchasing models (e.g., Krishna 1994a, 1994b; Meyer and Assuncao 1990), is that subjects often overbuy when exposed to small price promotions compared to optimal dynamic-models (e.g., Krishna 1994a, 1994b; Meyer and Assuncao 1990). Unfortunately, exactly why this bias arises is uncertain. One possibility, suggested by Krishna (1994), is that consumers generally underattend to holding costs, yielding a global tendency to overbuy. Meyer and Assuncao, however, found that because their subjects sometimes *underbought* relative to normative predictions they offered the alternative explanation that consumers deal with uncertainty about order quantities by relying on simplified ordering heuristics—such as, "when something is on sale, buy a little more than usual"—something that would yield overbuying given small price promotions, and underbuying given larger ones.

Toward positive theories of dynamic planning

The main value of experimental tests of normative decision models to date has been to suggest ways that such models, when used in field settings, may lead to biased predictions of choice. For example, a consistent finding of most experimental work is that subjects rarely seem to be able to strategically plan ahead for more than two periods in the future. This, in turn, suggests that empirical dynamic models that presume multi-period optimization are probably much more complex than they need to be in light of how consumers actually reason.

A tempting next stage for laboratory work in dynamic decision making would be to use such data as a basis for the development of a formal theory of heuristic problem-solving—a possible formal alternative to decision-theoretic models of dynamics. Exactly what such a theory would look like, however, is far from clear. A natural starting point might be to assume that individuals develop heuristic solutions to problems by performing an intuitive cost-benefit calculation; one considers alternative means of solution, and then chooses that which seems to offer the best trade-off between accuracy and ease of execution (e.g., Johnson and Payne 1985). The paradox of this approach, of course, is that such a cost-benefit calculation may be even more complex to execute than the original normative problem it was meant to approximate, and hence, even less compelling as a behavioral account of how dynamic decisions are made.

Yet, there is encouraging evidence that normative cost-benefit models may, in fact, provide a useful approach to modeling the selection of dynamic decision heuristics. For example, choice heuristics adapt to changes in task complexity (such as set size) in a way that is generally consistent with a cost-benefit analyses of choice rules (e.g., Johnson and Payne 1985).

Perhaps where this approach has been most extensively applied has been to the problem of modeling consideration-set formation. Given a large set of options, it has been widely observed that individuals do not evaluate all alternatives, but rather focus on a reduced set of viable options. A number of models of consideration-set formation have been proposed, all presuming that the selection process involves an intuitive cost-benefit calculation by consumers—new options will be added to a set if the benefits of adding a new option exceed the cost of added processing. In particular, if U_i refers to the conjectured utility of some option i, the consumer is assumed to perform the calculation

$$E[max(U_1,U_2, \ldots, U_{k-1},U_k) - max(U_1,U_2, \ldots ,U_{k-1})].$$

If the value of this difference surpasses some minimal level, the consumer 'admits' the k^{th} alternative to the consideration set (e.g., Feinberg and Huber 1996, Hauser and Wernerfelt 1990, Soofi and Gensch 1995). This minimal value is typically referred to as 'cost', which is taken to include financial, cognitive, and temporal senses of the term.

Are consumers optimal in the use of suboptimal heuristics? Focusing on the above calculation in a dynamic setting (i.e. sequential presentation of alternative automobiles), Buchanan, Sen, and Steckel (1996) found results consistent with the by-and-large rational with systematic exceptions theme. Subjects were able to perform the calculation for 71% of the admit-reject decisions they were faced with. Errors could be explained by uncertainty of attribute levels (subjects avoided it) and the attribute levels of the alternative in question relative to those of the alternatives already in the consideration set.

Beyond dynamic programming: the self-management of preferences

In the work we have discussed to this point it has been assumed that while *choices* made over time may exhibit serial dependencies, the *preferences* consumers that underlie these choices are nevertheless stable. That is, while we may switch among options to gather information about their quality, or refrain from buying out of a belief that lower prices can be obtained in the future, the assumption has been that the preferences that drive these behaviors remain stationary. There is, however, an emerging stream of behavioral research that suggests that preferences may be as much a *consequence* of choice as a determinant of them. Specifically, consumers may make choices so as to yield a preferred set of preferences (e.g., Gibbs 1996).

A formal treatment of such self-management has recently been offered by Bodner and Prelec (1996), termed *self-signaling theory*. Self-signaling theory is rooted in an assumption that people derive utility from the diagnostic implications of their choices—what the choices imply about their preferences, abilities, dispositions—even when the choices have no causal impact on these unobserved internal characteristics. For example, a person might behave recklessly just to prove to themselves that they are a "bold decision maker," or, conversely, might avoid even sensible gambles out of fear of revealing a gambling disposition.

Although self-signaling was not developed as a theory of dynamic choice *per se*, it nevertheless leads to some novel interdependencies between past choices and current ones. These interdependencies stem from the fact that a self-signaling individual is vulnerable to "moral placebo effects," where a change in mere beliefs about one's traits or abilities affects preferences over different courses of action. Because one's past choices are an important source of evidence about one's traits or abilities, these choices can become binding precedents even when the rationale for doing the same thing is no longer valid. Thus a person who only buys clothes on discount might decline to pay full price for an otherwise reasonably priced item just so as to preserve a perfect buying record, and the self-image of the "prudent consumer" that such a record sustains. To such a person paying full price might be a disturbing signal of financial irresponsibility.

Because any individual decision is a potential precedent for subsequent decisions, self-signaling endows each choice with more significance that it would have if evaluated in isolation. Empirical work is needed in this area.

Discussion

The study of choice dynamics—in one form or another—has occupied considerable research energies in at least three disciplines (economics, marketing, an psychology) over the past forty years. In light of this, what is perhaps most surprising about work in the area is how little we still seem to know, and how fragmented our existing knowledge tend to be. For example, while the study of learning has been a major preoccupation of experimental psychology since the turn of the century, panel-data models recognizing learning are still in their embryonic stages. In many cases, all we seem to be able to say is that behavior on one occasion will be conditioned by the behavior on the last, and that we can measure this dependency—hardly a profound theoretical achievement. Likewise, for all the effort that economics has devoted to the development of normative dynamic decision theory (and game theory) since the 1950's, we remain largely in the dark about how consumers actually incorporate expectations about the future when making decisions, and hence how should one best specify dynamic-structural models.

Why has progress been slow? One reason is that work in the area has suffered from a creeping parochialization, where work in different areas of dynamics proceeds with little attention given to its relation to work in complementary areas. For example, consider a problem we discussed earlier: how should an applied modeler specify dynamic-structural models for panel data (e.g., Erdem and Keane 1996)? Almost all work in this area starts with an assumption that both experimental economists and psychologist would argue is false: that consumers solve problems as optimal dynamic decision makers, following the principles of stochastic-dynamic programming. But for all the empirical evidence that might support this criticism, behavioral researchers in experimental economics and psychology that have not come forward with an alternative basis for modeling. Work in experimental economics has become increasingly taxonomic in nature, and researchers in cognitive psychology have displayed little interest developing models that might be used in applied field research. On the other hand, it is also true that econometricians could be said to make little real attempt to learn from behavioral developments in either psychology or experimental economics.

Yet for all these shortcomings, work in dynamic decision making across fields has yielded points of communality that we hope will serve as focal points for interdisciplinary work in the future. There is, for example, emerging agreement that the field is not well served by the historical emphasis of modeling dynamics by adding state dependence to an otherwise static representation. Depending on the problem context, while consumers may well maximize utility when making choices, it is a utility that is formed mindful of what has been learned from past choices, and how different current choices will affect the utility to beg gained from choices made in the future. Where the great challenge lies is in developing representations of this general maximization process that are both useful in applied settings and have a firm footing in behavioral theory. The research we reviewed on case-based decision theory is a good example of work that achieves this synthesis, and it serves as a good illustration of how future work in the study of choice dynamics might proceed.

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