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Process and Context in Choice Models

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Abstract

We develop a general framework that extends choice models by including an explicit representation of the process and context of decision making. Process refers to the steps involved in decision making. Context refers to factors affecting the process, focusing in this paper on social networks. The extended choice framework includes more behavioral richness through the explicit representation of the planning process preceding an action and its dynamics and the effects of context (family, friends, and market) on the process leading to a choice, as well as the inclusion of new types of subjective data in choice models. We discuss the key issues involved in applying the extended framework, focusing on richer data requirements, theories, and models, and present three partial demonstrations of the proposed framework. Future research challenges include the development of more comprehensive empirical tests of the extended modeling framework.

Keywords: decision making process, context, social networks, econometric models, subjective data

1. Introduction

In general, a choice is the outcome of a stream of evaluations of expectations and potential strategies, or more generally of a planning process. Shopping, for example, will usually be preceded by a planning stage that may include a review of needs and budgets and preparation of a tentative shopping list. Moreover, individual decisions are often not made in isolation. Choice interdependences occur in family as well as in broader social contexts. Similarly, a choice made at a given point in time is likely to depend on previous choices. Finally, underlying attitudes and perceptions may play a crucial role.

In contrast with this real world complexity of choice behavior is the simplified representation used in mathematical structures employed to model these choices. At the most basic level, these models explain choices solely through interactions between measured attributes of the various alternatives available to the decision maker and his/her estimated sensitivities. Other factors, such as those listed above, are for the most part not explicitly modeled and need to be captured solely by the error term of the model.

To highlight the differences between real world behavior and typical representations in mathematical models, let us consider a number of complex examples.

Conventional approaches to decision making seem inadequate in explaining the persistence of the gap in educational attainment between black and white students, where these cannot be explained solely on the basis of differences in school quality or credit constraints [1]. Rather, it seems that this underinvestment by blacks in education can be explained by cognitive and noncognitive skill differences that emerge between blacks and whites in early childhood (see e.g. Carneiro et al. 2005). Focusing on adolescents, Ogbu (2003) discusses the adverse social consequences that educational achievement may have as it is perceived as representing "acting white". This proposition has implications for the modeling of choice. Akerlof and Kranton (2002) show how acting white may be understood when preferences incorporate self-image and desired identity, suggesting that the desired identity for many African Americans does not include educational achievement to the degree found for other groups. This leads to the question of why desired identities evolved this way and how social factors determine both desired

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[1] See Neal (2006) for evidence on these claims.

identity and actual self-image. Standard modeling approaches are not suitable in this context where an appropriate representation of social norms and expectations is required.

As alluded to above, a large number of decisions are made involving multiple agents, or affect more than one person. An important policy question in many countries is whether it matters to which member of a poor household benefits should be paid. Empirical studies invariably conclude that the recipient's identity matters, and that paying benefits to the wife generally increases the share of expenditures devoted to children. This conclusion is incompatible with the standard representation of household behavior, which is based on a 'unitary' model with a household behaving as a single decision maker maximizing a unique utility function under a budget constraint. This approach omits all issues related to 'power'. A possible (and natural) interpretation of the common empirical finding that the gender of the recipient does matter is in terms of shifts in the balance of power between spouses: when the wife receives the money, she has more control over its use. The standard, 'unitary' model of household behavior is too simple to account for such phenomena.

We also mentioned above how the choices made by other members of society may have an influence on a given individual's decisions. A canonical example of an individual decision that is influenced by social context is the adoption of an innovation. Innovations such as computer operating systems exhibit the property of network externalities, which essentially means that the payoff to one person of adoption of the innovation is an increasing function of the number of population members that have already adopted. This interdependence has powerful implications for the way that an innovation diffuses. Models of innovation diffusion such as the Bass model in marketing (Bass 1969) appear throughout the social sciences and bear a close relationship to epidemiological models in public health. However, the specific processes and behavioral traits accommodated by such models are once again typically ignored in standard models for analyzing choices.

The above examples have highlighted the richness of real world behavior. The research community is gradually starting to appreciate the importance of factors such as interactions between decision makers, the actual processes leading to a choice, and the role of subjective factors. As a result, new models are emerging that give a more realistic representation of real world behavior, such as accounting for the compromise effect related to intermediate options in a choice set (Kivetz et al. 2004), reference dependence (Kahneman and Tversky 1979), and social influences (Brock and Durlauf 2001). In this paper, we develop a framework to accommodate a broader view of choice models. We enrich choice models by explicitly representing the context and process leading to a choice. Process refers to the steps involved in decision making. Context refers to factors affecting the process. We demonstrate how the enhancements of choice models with explicit representations of context and process can lead to new insights.

This paper summarizes the work of a workshop at the 2010 Choice Symposium to develop insights into how enhancements of choice models with explicit representation of context and process address known violations of rationality. It extends the developments in the paper from the 2001 Choice Symposium workshop which developed the Hybrid Choice Model (HCM) that incorporates aspects of behavioral theories (such as attitudes, perceptions, decision protocols, etc.) into the random utility model of choice (Ben-Akiva et al. 2002). The extensions in this paper which aim at adding more behavioral richness to the HCM include the explicit representation of the planning process preceding an action, the effects of context (family, friends, and market) on the process leading to a choice, and the dynamics in the process of decision making, as well as the inclusion of new types of subjective data in choice models (such as expectations and subjective well-being).

Section 2 presents a conceptual framework for incorporating process and context into choice models. Section 3 discusses implications for empirical and theoretical work, focusing separately on data collection, theories, and modeling. Section 4 concludes.

2. Framework

This section presents a framework that describes the steps of the decision making process, the different types of contexts and their characteristics, and the mechanisms through which process and context interact to affect decisions.

2.1 The Process of Decision Making

The standard economic consumer model treats the decision making process as a "black box". It explains choice behavior simply by a set of preferences ranking of all potential outcomes, where the consumer is assumed to choose the most preferred available outcome. Under certain assumptions consumer preferences can be represented by a utility function such that the choice is the utility maximizing outcome. Preferences and utility are unobserved but the researcher can make inferences about preferences based on the observed choices of consumers.

The description of consumer choice behavior can be given more structure by describing choice behavior as a decision making process involving a sequence of steps. Various representations of this process have been suggested by behavioral researchers. Figure 1 presents one stylized view of some key elements of this process.

Individuals recognize opportunities and constraints regarding the behavior in question. They collect and filter information about the attributes of available options which, together with their attitudes and emotional states, influences their perceptions and beliefs about these options. Individuals then focus and refine their preferences, targets, and needs, and form a plan for the decision. The plan can be thought of as a strategy, decision criterion, or intention. Different alternatives are evaluated and the decision is executed following the plan. Individuals then reflect upon and learn from the realized outcomes and subsequently update their perceptions and plans. In Figure 1, the arrow going out of the choice box refers to the dynamics in the process of decision making.
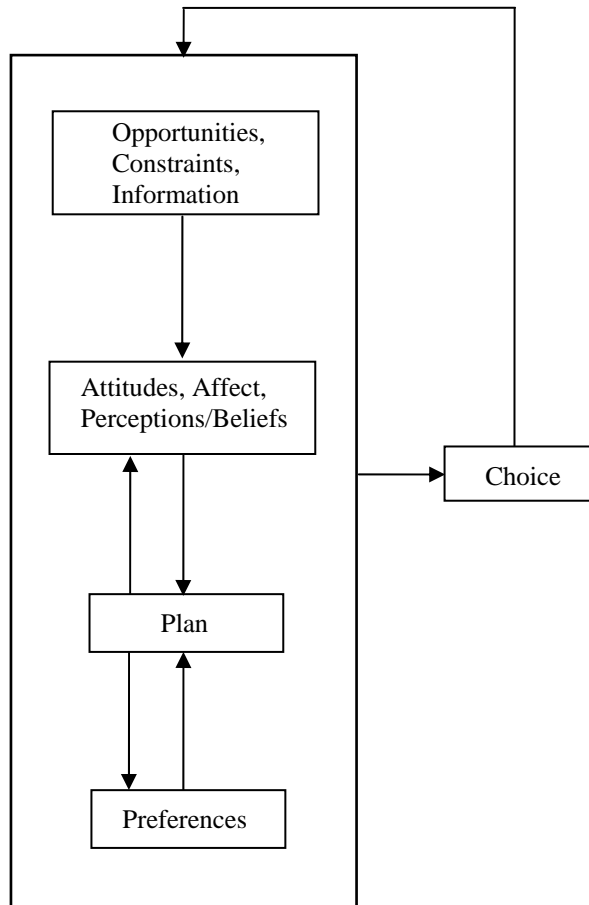
Figure 1. The process of decision making (adapted from McFadden 1999).

2.2 The Context of Decision Making

The context of decision making is here understood loosely as consisting of all other individuals. A useful way to structure the context is through the concept of social networks. Individuals generally belong to a number of social networks. They may be small or large and include few or many members. It is useful to distinguish between tight and loose social networks.

Tight social networks have few members, strong interactions between members, and high entry and exit costs. Examples are groups defined by family relationships or close friendships. Tight social networks exhibit strategic interactions, joint constraints, and joint production. Loose social networks have low entry and exit costs. They are larger and involve weaker interactions between members. There are many examples of loose social networks, such as friends, online networks, neighborhoods, ethnic groups, classrooms, clubs, professional networks (e.g. close working colleagues), etc. The size of loose social networks implies that the potential for strategic interaction is small. There are, however, a range of possibilities for non-strategic interactions, including information acquisition, emulation, reciprocity, adherence to group norms, etc., that may affect decisions as discussed in the next section. In most cases,

membership in loose social networks is endogenous. It is possible to think of markets in which many individuals participate as very loose social networks. In this perspective, demand-supply equilibration is a social interaction. Entry and exit costs tend to be low and there are only weak interactions between members.

2.3 The Interaction of Process and Context

There are various mechanisms through which the different social contexts described in the previous section impact the various steps of the decision making process. A framework for the interaction between process and context, leading to a choice, is shown in Figure 2. The various interaction mechanisms and the specific steps of the decision making process that are impacted are described in this section separately for tight social networks, loose social networks, and markets.
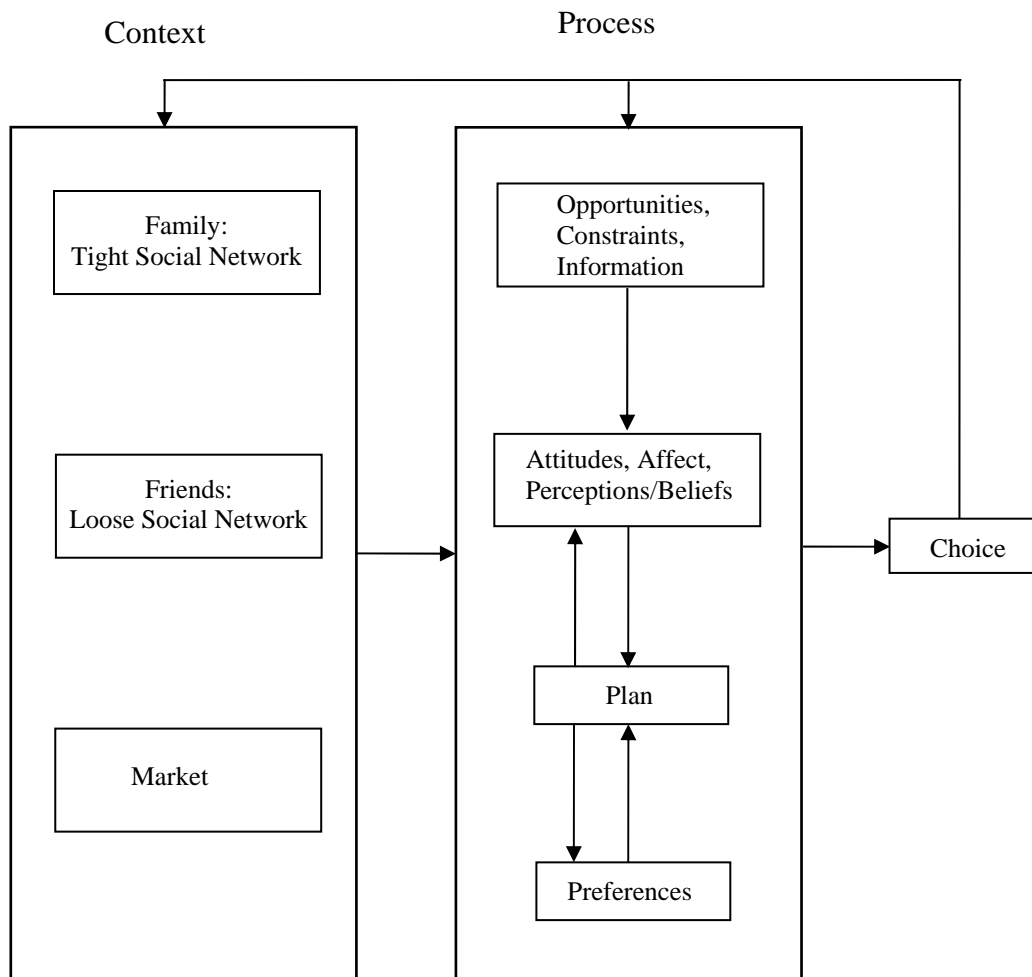
Figure 2. Interaction of process and context.

2.3.1 "Family": Tight Social Network

Tight social networks may affect individual decisions in various ways. First, members of tight social networks may engage in joint production or they may face joint constraints such as household level budget constraints for monetary expenditures or the use of the family car. Another example is the joint production of a family holiday, in which family members cannot make decisions in isolation. A second mechanism is altruism, where the well-being of others within a family clearly matters for choices. Third, the small size and the strength of the group interactions creates a potential for strategic interaction, where the decisions of an individual depend not only on his/her own preferences but also on his/her anticipation of the reaction from other group members.

As discussed in Section 1, the unitary model, which assumes that the family behaves "as if" there were a single (usually benevolent) decision maker, is not relevant for understanding, modeling, predicting, and influencing family decisions. Alternative modeling approaches are needed (see Section 3.2.2).

2.3.2 "Friends": Loose Social Network

In economics, social influences are often called social interactions; see Blume et al. (2010) for a recent survey and Jackson (2008) for a review of the complementary literature on social networks. Unlike the family context, it is natural to think of the equilibrium choices of the group members as determined noncooperatively.

Social interactions can arise at each of the various steps in the decision making process and arise from several distinct mechanisms. First, individuals may use the behaviors of others to learn about the characteristics and desirability of choice options. Imitation may also save individual cognitive effort in computing the optimal choice in complicated situations. Second, there may be direct payoff effects. The utility of an activity such as smoking may depend on whether one's friends smoke as well. Alternatively, social norms can influence the payoffs associated with actions such as nonmarital fertility or transit ridership. In this case, an important question is whether the norm is internalized, so that utility is directly reduced by the existence of the norm, or whether the norm induces undesired consequences such as shunning by others. Third, some costs or other constraints may be socially determined. At a tactical level, the driving maneuvers that an individual can make (whether to switch lanes, speed up, or slow down) are based on both realized and anticipated actions of other drivers. Further, drivers make decisions on when and where to drive that are influenced by the traffic patterns they will experience. In this respect, the social interactions a driver experiences are themselves the outcome of choice. These two levels consolidate into congestion on the roads, which then is a feedback mechanism to influence future driving choices.

Social interactions matter both because they expand the domain of determinants of individual choice and because they can qualitatively affect aggregate outcomes. Interdependences of choices can produce multiple equilibria in the collections of choices in a population. The presence of social interactions can create complicated implications for the effects of policy changes. The direct effects of changes in individual incentives on individual behaviors will, via social interactions, create further changes in behaviors. As a result, the effects of policy changes can be highly nonlinear. Social interactions also have implications for the desirability of interventions to influence choices. Manski (2010) presents an example in which individuals would make diverse choices in the face of uncertainty; a mechanism imposing identical choices would increase average utility.

The driving example illustrates a second dimension along which social factors affect choice: namely individuals make choices based on the social interactions that will result. Drivers choose routes based on the expected interactions they will experience will other drivers. Families choose neighborhoods because of the anticipated social interactions effects on children. A complete theory of the effects of social factors on a given choice requires the modeling both of the direct effects of groups on choices as well as the way that these effects influence group membership decisions. An example of how one can proceed to do this using a nested logit model is found in Brock and Durlauf (2006) but the interplay of these two levels of choice is much underresearched.

2.3.3 Market

Markets bring together demanders and suppliers of products to trade in mutually beneficial ways. The simplest analysis of a market setting, and the mainstay of most applied work to date, consists of three primitives: (i) a demand function for products, generated by aggregating the demands of the individuals in a market, (ii) cost functions for the firms producing those products, and (iii) an equilibrium assumption (such as Nash in prices or quantities).

The standard equilibrium framework has been applied to analyze increasingly complex market settings such as insurance markets. There are, however, market situations where standard equilibrium notions are suspect. Two important examples are (i) vertical markets where there are a small number of agents on each side and it is unreasonable to assume that one side sets price and the other simply reacts; these markets occur both in the distribution of manufactured products and in services (e.g. the HMO-hospital market), and (ii) markets where pricing is a dynamic phenomenon and it is unreasonable to assume that firms do not consider the impact of current prices on future profits; examples include markets for durable goods, experience goods (e.g. prescription pharmaceuticals), network goods (e.g. software platforms), and markets where search costs, or learning by doing, is important. So these markets comprise a considerable part of the economy.

There is a historical reason for this timing of developments. The game theoretic models of markets which were prevalent in the 1980's, though more realistic in important ways than the models that preceded them, delivered very little in terms of robust predictions at the level of detail needed for either policy analysis or for the understanding of historical episodes. The more detailed results, even conditioned on the simple static frameworks and the standard notions of equilibrium used in the applied game theory literature, depended on the form of the demand and cost functions. As a result, there was a push to develop techniques to uncover those forms, and empirical work simply applied the notions of equilibrium used in the applied theory literature. Existing theory is much less helpful in analyzing the more complex markets referred to above. There is no generally agreed upon equilibrium notion for vertical markets (at least when there is more than one agent on each side of the market). Moreover, the standard equilibrium notion for the analysis of dynamic models, subgame perfect Bayesian equilibrium, requires all market participants to have supernatural abilities both to retain information and to make computations.

There is a need to think about the process leading to market equilibrium in analyzing these more complex markets. What bargaining rules or game forms are appropriate in which institutional settings? How do agents learn from past experience and what information do they use in making decisions in relatively new situations? How do agents make decisions in situations where they know they lack much of the knowledge required to make accurate predictions? How do agents form perceptions on the likely actions (and reactions) of their competitors? What is a reasonable notion of an equilibrium point where all feasible deviations lead to a perceived fall in utility?

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3. Approaches

In Section 2, we have highlighted the possible role that process and context and their interactions play in shaping decisions and how this contrasts with standard modeling approaches. In the following we discuss the key issues facing any attempt to predict choice behavior that explicitly models the above aspects of process, context, and their interactions. We focus on data, theory, and modeling requirements.

3.1 Richer Data

3.1.1 The Problem of Inference on Decision Processes from Data on

Observed Choices

The standard practice to predict choice behavior, called *revealed preferences analysis*, has been to infer decision rules from data on observed choices. These inferences are then used to predict behavior in other settings.

Use of the term *revealed preferences analysis* to describe empirical analysis of choice data has become imprecise. Most empirical research today concerns choice problems in which decision makers act with partial information. The common assumption is that persons form expectations for the unknown outcomes of alternative actions and maximize some function of these expectations (e.g., expected utility maximization under uncertainty or minimization of maximum regret under ambiguity). Hence, the research problem is not only to infer the utility functions that embody preferences over outcomes but also to infer the expectations that persons hold and the decision criteria they use. In situations with social interactions, the analysis also requires inference on the structure of the reference groups (or networks) that affect behavior and on the nature of the interactions.

Observed choices may be consistent with many alternative specifications of preferences, expectations, social interactions, and decision criteria. Hence, identification of decision rules from choice data alone must rest on strong maintained assumptions. A prevailing practice in the analysis of individual behavior has been to assume that decision makers have specific expectations which are objectively correct (i.e., rational) given the information they possess and that they maximize expected utility. In the analysis of choice with social interactions, it has been common to assume specific structures for reference groups and for the nature of the group interaction.

These assumptions reduce the task of empirical inference to revelation of preferences alone. However, researchers often have enormous difficulty defending the assumptions they maintain. Thus, choice data alone often do not suffice to credibly infer how persons make decisions. See Manski (2004) for further discussion of these matters.

3.1.2 Collection and Analysis of Subjective and Experimental Data

We believe that the inferential enterprise may be improved by the collection of relevant subjective data alongside of choice data, and by the integrated use of subjective and choice data to estimate structural models of decision making. Many forms of subjective data may be helpful. These include:

- Expectations Data: A modern literature collecting expectations data in the form of subjective probability distributions was initiated in the early 1990's. It has by now matured to the point that such data are increasingly being used in formal discrete choice analysis, both in field settings and in experimental economics. See Manski (2004) for a review of the literature and Delavande (2008) for an exemplary application to discrete choice analysis.

- Data Characterizing Reference Groups and Social Networks: A number of studies have directly asked individuals to characterize the individuals with whom they interact in specified settings (e.g. Carrasco et al. 2006; Coleman et al. 1966; Keating et al. 2007) but this type of data collection is not very common for choice modeling purposes.

- Data Characterizing Individual and Group Decision Criteria: In general, individuals making decisions with partial knowledge are not currently asked about the criteria they use. Nor are groups making collective decisions asked to characterize the group decision process. It may be highly useful to elicit such information.

- Data on Subjective Well-Being: So-called "happiness" data are collected often, but they typically are not used in formal modeling of choice behavior. They may be helpful for this purpose.

A necessary caveat is that collection and analysis of subjective data should not be approached naively. There are important open issues regarding the information obtained from various measurement approaches. There are similarly open issues regarding the relationship between the data obtained and the subjective concepts of behavioral interest.

Data on decision making processes could also be enriched by laboratory experiments. Some concepts are hard to define in a non-experimental context. For example, the concept of ambiguity is itself ambiguous. How to explain rigorously why a player faced with an urn containing red and black balls will systematically appear more risk averse when the fraction of balls of each color is unknown (uncertainty) than when it is known (risk)? The experimental setting helps researchers in developing a model of ambiguity and its relation to risk aversion. These methods are also being applied to situations with social interactions. Bateman and Munro (2005) present results of an experiment designed to investigate to which extent decisions made by couples and decisions made separately by spouses are consistent with the axioms of expected utility theory. They find that choices made by couples are typically more risk averse than choices made by individuals. However, experiments conducted by de Palma et al. (2011) in Germany, and later on by Picard and de Palma in France suggest that decisions made by couples are more rational (that is, fewer violations of transitivity are observed) than decisions made by individuals.

3.2 Behavioral Theories: Interface of Psychological, Sociological, and

Economic Explanations

The challenge of the richer conceptualizations of choice we have described both in our examples and in our elaboration of the process of decision making is the instantiation of the richer psychological and sociological theories into formal economic frameworks that are amenable to econometric analysis. Our view is that psychological and social factors should complement and extend, rather than replace the choice-based perspective of economic theory. Put differently, we are interested in augmenting the determinants of preferences, constraints, and beliefs beyond those that are conventionally used in choice models.

From the perspective of social science theory, the formal instantiation of psychological and sociological factors into choice models is important for three reasons. The first and admittedly banal reason is that economic theory imposes logical consistency requirements that facilitate the development of increasingly rich versions of the choice models we advocate. A second, less obvious reason is that by thinking of choices as equilibrium outcomes, nontrivial general equilibrium effects can emerge. Our third reason is the desire to incorporate in formal modeling the insights gained from recent findings in behavioral and social economics.

Various behavioral theories focused on the process of decision making have been discussed in the literature and used to enhance the development of choice models, but less emphasis has been placed on behavioral theories related to context in choice modeling. We describe below two behavioral theories related to context - social interactions and family decisions - and some of the associated modeling issues.

3.2.1 An Example: Social Interactions

One theory that is well established relates to social interactions models, starting with Brock and Durlauf (2001). In this model and its generalizations, the existence of socially undesirable, but individually rational equilibrium configurations of choice is determined by the interplay of the strength of private incentives, the strength of social influences, and the degree of heterogeneity across individuals. Small changes in the factors can lead to qualitative changes in the nature of equilibrium. We conjecture that similar findings may hold when one considers how greater psychological richness is incorporated in the decisions of interdependent agents.

In emphasizing that new models should develop in ways that render them econometrically implementable, we are especially concerned about issues of identification. Richer conceptions of choice will not affect general social science thinking unless empirical evidence of their relatively superior explanatory power is demonstrated, and this will require that psychological, social, and "conventional" economic explanations are not observationally equivalent. Understanding the conditions under which observational equivalence breaks down is thus essential. In the case of social interactions, identification has been systematically studied; the literature starts with Manski (1993) and is synthesized in Blume et al. (2010). Manski (1993) introduced the "reflection problem" which describes the identification problems that arise when one attempts to distinguish whether the characteristics or behaviors of others are the carriers of social influence. Blume et al. (2010) delineate how self-selection and unobserved group-level heterogeneity can preclude identification even when the reflection problem does not arise and describe strategies for addressing these factors. Behavioral economics has generated little formal work on identification. In fact, Manski (2002) shows that the use of laboratory data does not obviate the need for formal identification analysis. The conditions under which psychological and social deviations from conventional economic models of decision making are identified in laboratory settings is a completely open area of research.

3.2.2 An Example: Models of Family Decisions

Another theory of interest is that of family decisions. Since the 1980's, unitary models have been increasingly challenged by two types of models of decision within the family. Strategic models assume that the interaction between family members is noncooperative (see, e.g., Chen and Wolley 2001), whereas collective models assume that this interaction is cooperative and therefore leads to a Pareto-optimal outcome. The hypotheses that spouses know each other and make Pareto-optimal decisions can be directly tested in the laboratories (see Section 3.1.2). Any model used for such studies should allow for differences in preferences between family members, but also for 'caring' or 'altruism' between them; it should distinguish between commodities that are privately consumed by each individual and those whose

consumption is public within the household; it should encompass household production and the related decisions; and it should, explicitly or axiomatically, model the decision process itself. A large body of literature, the so-called collective model of household behavior, has developed over the recent years as a response to precisely these questions (see, e.g., Chiappori 1988, 1992 and Browning and Chiappori 1998).

The basic collective model, introduced by Chiappori (1988, 1992) and Browning and Chiappori (1998), adopts an axiomatic approach: decisions within the household are only assumed to be Pareto efficient. Strong testable restrictions are generated for very general preferences (including general form of altruism, merit goods, paternalistic preferences, consumption externalities, household production, and others). Moreover, such restrictions, which directly generalize the Slutsky conditions of standard consumer theory, tend not to be rejected by the data. In this setting, the notion of 'power' has a natural translation in terms of Pareto weights; for instance, any change in the economic environment that increases the wife's weight without changing the husband's improves her bargaining position (her 'power'), and the resulting changes in household decisions can readily be modeled.

The model can also be specialized to the case of caring preferences. Here, each member is characterized by a selfish sub-utility and an altruistic (caring) utility, which may depend on the selfish sub-utilities of all household members. In that setting, efficiency has a simple interpretation: household members act as if they were following a two-stage program. In the first stage, expenditures on the commodities publicly consumed are decided, and the remaining nonlabor income is shared between members according to some (conditional) sharing rule. In the second stage, each member optimally chooses her own labor supply and private consumption, based on her own preferences. The main benefit of caring preferences is that it is in general possible, under a simple exclusion restriction, to identify individual subutilities from the household's aggregate behavior. In Chiappori's (1992) model of collective labor supply with private consumption, the observation of individual labor supplies and household joint consumption allows to recover individual preferences as well as the sharing rule, up to an additive constant term. This result has recently been extended to labor supply with public consumption by Blundell et al. (2005) and to a fully general setting by Chiappori and Ekeland (2009). Finally, specific attention has been devoted to the collective decision process in the case of household production (see Apps and Rees 1997).

The collective approach provides a framework for addressing issues linked to the targeting of specific benefits or taxes. Children provide a typical example of both public good and household production. Coming back to the example in Section 1, paying a benefit to the wife instead of the husband will, from a collective perspective, boost her Pareto weight; the resulting shift has an impact on household behavior, that can readily be estimated.

3.3 Structural Models and Econometric Methods

We now turn our attention to ways of expressing the above theories in the context of econometric models. These models explain the way in which the 'outcome' can be modeled subject to technological, regulatory, and/or social constraints (club or family rules, equilibrating conditions in a market, etc.), making use of model-specific behavioral assumptions.

Each of the parts of the model may contain variables that are not observed by the researcher. It is useful to distinguish between two types of unobservables: those known to the agent when it makes its decisions and those that are not. In this paper, we focus on the decision making process (as represented by plans, decision protocols, etc.) that is in itself unobservable as are certain elements of the decision making context (such as reference groups and field effects).

Unobservables known to the agent when it makes its decision lead to a correlation between the choice variable and the unobservable, which can lead to an endogeneity problem. Unobservables of the second type will cause an endogeneity problem when the outcome variable itself appears as an explanatory variable in the system estimated (e.g. substituting realized profits for expected profits). Just as the outcome functions, beliefs, and constraint sets may be related across agents, so may the unobservables be related. When this is the case, and there is an endogeneity problem, to solve that endogeneity problem we will often have to incorporate the interactions among the various agents explicitly. We will return to the endogeneity issues in more detail in one of our examples below.

A related point of interest is the dynamics of how the primitives of a model evolve. Typically this will include the processes by which outcome functions, perceptions, plans, and constraints evolve over time. This is exemplified by the dynamic plan and action model described in the following section.

We next present three examples. The first relates to the use of subjective well-being data in choice models. The second is the above mentioned plan/action model that deals with the dynamics of unobserved processes that underlie decisions, and the third example shows how field effects arising from social interactions can be included in choice models and how endogeneity can be accounted for.

3.3.1 An Example: Subjective Well-Being Data

We present an example of using subjective data alongside of choice data. The example pertains to the use of subjective well-being or happiness data to extend random utility models. The modeling framework, developed in Abou-Zeid and Ben-Akiva (2010), uses measures of subjective well-being as indicators of utility in addition to the standard choice indicators, and explicitly distinguishes among various notions of utility such as remembered, moment, and decision utility (Kahneman et al. 1997). The framework was applied to model mode choice decisions, using data from an experiment conducted at the Massachusetts Institute of Technology (MIT), whereby a sample of MIT employees who habitually commute by car agreed to commute temporarily by public transportation in return for a free public transportation pass. After this treatment, the participants' mode choice decisions for the commute to work were recorded. In addition, data on their happiness with the commute to work were obtained pre-treatment (for the car) and post-treatment (for car and public transportation).

The combined choice-happiness model was specified as follows. The structural model specified pre-treatment car utility, post-treatment car utility, and post-treatment public transportation utility of the form $U_i^t = V_i^t + \varepsilon_i^t$, where t indexes the time period (pre-treatment or post-treatment), i refers to the mode (car or public transportation), U is total utility, V is systematic utility, and ε is an error term.

The measurement model consisted of a choice equation based on post-treatment utility maximization and three happiness equations. The happiness equations express the pre-treatment and post-treatment happiness measures as a function of the corresponding utilities, $h_i^t = \lambda_i^t U_i^t + \upsilon_i^t$, where h is a happiness measure, λ is a parameter, and υ is an error term.

Thus, the new modeling framework adds a happiness measurement model to a standard choice model. The estimation of this model using the MIT data demonstrated that the extended choice-happiness model is consistent with the choice-only model, but that the model that includes happiness indicators is more efficient.

3.3.2 An Example: Dynamic Plans and Actions

In many situations, observed actions are preceded by unobserved plans representing intentions, decision protocols, etc. The plans are known to the agent but are unobservable by the researcher. For example, in the context of driving behavior, the plan may represent the target lane that a driver wishes to be in, and the action represents the gap acceptance decisions a driver makes as he/she tries to move to the target lane. Modeling plans is useful because the dynamics of actions is then given by the dynamics of the underlying plans. A framework for representing these dynamics is shown in Figure 3, where l_t denotes the plan at time t, j_t denotes the action at time t, and T is the time horizon.
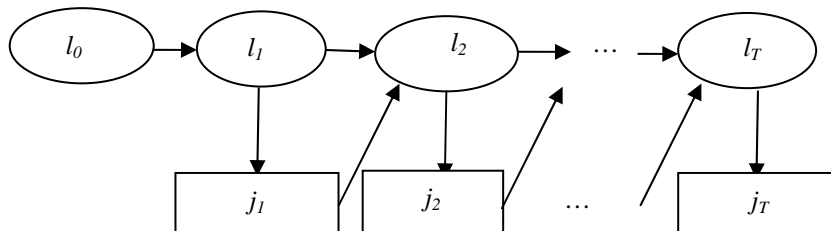

Figure 3. Dynamic plan/action model (Ben-Akiva 2010)

We use the Hidden Markov Model assumptions to simplify the specification of the model. The first assumption is that the action at time t only depends on the plan in effect. The second assumption is that the plan at time t depends only on the plan at time t-1, and may also depend on all historical actions. The probability of a sequence of plans and actions can then be expressed, and the probability of the observed sequence of actions can be obtained by summing over all possible sequences of plans. This sum is simplified by the Hidden Markov Model. See Ben-Akiva (2010) for more details.

A recent application of the above framework to modeling driving behavior (Ben-Akiva 2010) demonstrated that the model that includes plans and their dynamics is better able to predict lane changing and merging maneuvers under congested situations as compared to a reduced form model that does not represent planning behavior.

3.3.3 An Example: Social Interactions and Transportation Choices

One approach used to capture social influences in discrete choice models is to incorporate a "field effect" variable into random utility models (developed by Brock and Durlauf 2001, 2006). A field effect variable captures social interactions by defining peer groups and allowing each person's choice to depend on the overall choice probabilities of the other people in his or her peer group. The field effect is defined as the percent of people in the peer group exhibiting a given behavior. Denoting this field effect as F, the utility U of a given alternative i for a given decision maker n is

$$U_{in} = V(x_{in}, s_n; \beta) + \gamma F_{in} + \varepsilon_{in},\tag{2}$$

where $V(x_{in}, s_n; \beta)$ is the systematic portion of the utility (consisting of attributes of the alternatives x_{in}, characteristics of the decision maker s_n, and taste parameters β), F_{in} is the proportion of those people in the peer group of decision maker n who chose alternative i (and γ is a parameter that captures the strength of the influence), and ε_{in} is the unobservable portion of the utility.

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Fukuda and Morichi (2007) provide an example of social determinants of transportation choice, analyzing Tokyo commuters' illegal on-street bicycle parking behavior. Despite efforts to increase legal parking opportunities, widespread illegal parking persists. Fukuda and Morichi (2007) hypothesize that there might exist field/conformity effects among bicycle users in the choice of parking locations whereby the payoff that an individual receives from his/her choice depends on the choices of other members in his/her reference group. In this case, observing others park illegally could induce illegal parking behavior. Empirical results based on the Brock-Durlauf model indicate the existence of significant social interaction effects among bicycle users on illegal parking and a large variation in the aggregate share of illegal parking across different stations, which constitute reference groups.

An issue with the field effect formulation is that it may suffer endogeneity, because similar, unobservable environment and preferences impact both the decision maker being modeled as well as the behavior of the people in the decision maker's peer group. To address this issue, Walker et al. (2011) present an application that employs a field effect variable in a transportation mode choice context in which they correct for endogeneity using the Berry, Levinsohn and Pakes (BLP) procedure (Berry et al. 1995, 2004). BLP is appropriate when the endogeneity can be considered at a market level. In their mode choice example, the markets are peer groups, where these peer groups are defined based on spatial proximity and social class. The BLP process removes the endogeneity from the choice model via the use of market-specific constants. The endogeneity is then dealt with in a linear regression setting (with instrumental variables) to obtain consistent estimates of the social influence effect. This consistent estimate of the field effect parameter is then reintroduced to the choice model to obtain a choice model that captures social influences. Applying this procedure, Walker et al. (2011) found there was a significant upward bias of the field effect parameter γ when endogeneity is not corrected.

4. Conclusion

While a number of enhancements have been made to choice models, the majority of the developments have focused on improving the representation of the process of decision making, by explicitly accounting for example for factors such as perceptions, attitudes, decision protocols, plans, habits, etc. as well as for dynamics in the process and heterogeneity among individuals. Less emphasis has been placed on modeling the interaction between context, taken here to represent social networks, and the process leading to a choice. We motivated and illustrated in this paper the importance of explicit modeling of context and process in choice.

We proposed a modeling framework which extends the Hybrid Choice Model by explicitly representing the planning process preceding an action and its dynamics and the effects of context (family, friends, and market) on the process leading to a choice, and can include subjective data to enrich the choice models and ease their estimation. We concluded that richer data, behavioral theories, and structural models need to be developed, and provided a few examples of approaches that could be pursued. Richer data would entail collection of subjective data on expectations, reference groups and social networks, decision criteria, and well-being, and conducting experiments. Richer behavioral theories would provide a foundation for choice models that explicitly include psychological and social factors. Richer structural models would explicitly model such unobservable social and psychological factors.

The modeling examples we provided to illustrate the proposed framework were partial demonstrations of certain components of the framework: adding happiness measures in random utility models through happiness measurement equations where happiness is a measure of utility, representing the dynamics of actions by the dynamics of plans through a Hidden Markov Model, and representing the effects of social influences on mode choice by adding a field effect variable while accounting for

heterogeneity. The challenge that lies ahead for future empirical work is the development of a more comprehensive empirical test of the overall framework that includes social influences, better representation of the decision making process (e.g. by accounting for planning), and new types of subjective data (social networks, well-being, expectations, etc.).

A number of open research questions will need to be answered before bringing the overall framework into the realm of empirical testing. In terms of subjective data, important theoretical considerations include linking the data obtained to the subjective concepts of behavioral interest while properly accounting for biases and other errors in measurement. In terms of modeling the interaction of process and context, important areas of research include modeling the two-way interaction between choices and group membership decisions, further work on formal identification analysis and tests even with experimental data collected in laboratory settings, and further analysis of the process leading to market equilibrium in the types of complex markets discussed in this paper.

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