CHAPTER 14

CHOICE AND PROCESS: THEORY AHEAD OF MEASUREMENT

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A New Method

The traditional method of decision theory, founded on revealed preferences, restricts its focus to predicting and explaining *choice* and is agnostic about the *process* underlying choice itself. Recent research in economics (typically under the heading of "neuroeconomics" or of "behavioral economics") aims instead at developing joint implications on choice as well as on processes.

In this chapter, we argue that models of decisions designed to produce joint implications for both choice and process constitute a new and exciting area of research for decision theory.

We also argue, however, that the literature would gain from the adoption of structural empirical methods to guide the analysis and test the models. The conceptual hiatus between axiomatic decision theory in economics and models of decision processes in neuroscience in fact ~~necessitate~~ a structural approach to better lay out and clarify the often implicit identifying assumptions adopted in either discipline.

We finally attempt to illustrate, by means of examples in the context of intertemporal decision theory, how a structural analysis of choice and process can add explanatory and predictive power to decision theory.

Why a New Method?

The traditional method adopted in economics has its foundations in *revealed preferences.* It is the product of the ordinal revolution in I. Fisher [1892] and V. Pareto [1906].[1] This method has been most recently discussed by Gul and Pesendorfer (chapter 1) in a lucid and provocative manner as an alternative to behavioral economics and neuroeconomics.

In the pure example of this method, a decision maker is presented with choices among acts. An act describes the consequence that the decision maker will obtain for every realization of a state of nature. A theory of choice is a complete list of what the decision maker will choose for any possible option that she is facing. Since listing the choices obscures their systematic nature, the list is summarized in a set of axioms. The typical decision theory is then a representation theorem, that is, the statement that the decision maker chooses according to the axioms if and only if she chooses *as if* she were maximizing a certain value function.

In this view, the representation of the preferences has purely the nature of a conceptual construct and has no independent informational value in addition to what is already contained in the axioms. For the method of revealed preferences, the only admissible evidence to test a decision theory over a set of options is the agent's real choice from subsets of that set.

It is certainly good methodological practice not to test a theory based on data the theory itself was not designed to fit. As we do not reject representative agent macroeconomic models based on the observation of agents' heterogeneity, we should not reject the standard axiomatic decision theory if we fail to identify a max U process in the brain.

Nonetheless, we argue here that a clear-cut methodology making use of explicit models of process as well as psychological or neurophysiological data can provide the decision theorist with useful tools to explain choice. More specifically, we claim that, even if we agree that our objective as economists is to explain choice per se, not process, nonetheless the study of choice processes has in principle additional explanatory power for decision theory.

If, however, we find ourselves to date hard pressed to name existing models and data on decision processes that have fundamentally contributed to our understanding of choice, this is, in our opinion, because most empirical work in neuroeconomics is not tightly guided by models making joint predictions on choice and process. We therefore observe that, in practice, progress in producing explanatory power to understand choice is likely to require *structural analysis*, more theory ahead of measurement.[2]

Before proceeding with the arguments, we wish to clarify two terms we repeatedly use in this chapter, "*explain*" and "*structural analysis.*" By "*explain~~s~~*" we mean, with Gul and Pesendorfer (chapter 1), "identi~~fies~~ choice parameters [. . .] and relate~~s~~ these parameters to future behavior and equilibrium variables." In other words, an explanation is such when it has predictive power, outside of sample. By "structural analysis," we mean the specification of a formal model that maps a set of parameters, assumed stable, to a set of observable (measurable) variables, and the estimation of the parameters by statistical inference methods. The structure of the model explicitly represents the a priori assumptions underlying the analysis. In the context of the study of choice and process, a structural model has implications for both choice and process variables.

When Is Theory and Measurement of Process Useful?

The aim of this section is to examine the conditions under which economic analysis may be improved by theorizing about and observing psychological states and decision processes.

To set a frame of reference for the ensuing arguments, consider the typical decision problem in the spirit of revealed preference. A decision maker chooses from subsets A_1, A_2 of an abstract choice set $\mathbf{A}$. His behavior is formally represented by a choice function $C(\cdot)$ whose domain is the set of subsets of $\mathbf{A}$ and whose range is $\mathbf{A}$. Standard decision theory would study the implications, in terms of choice, of a series of axioms on choice itself taken to define rationality. The fundamental axiom of rational choice is *consistency* (a.k.a. independence of irrelevant alternatives):

$$\text{if } A_1 \subseteq A_2 \subseteq \mathbf{A} \text{ and } C(A_2) \in A_1, \text{ then } C(A_1) = C(A_2)$$

The choice function $C(\cdot)$ satisfies consistency if and only if it can be represented by a preference ordering $\geq$ such that $C(A)$ contains the maximal element of $\geq$ in A.

Notice that the explanatory power of standard decision theory results from an axiom such as "consistency" underlying (having predictive power regarding) choice in many different environments, for example, from intertemporal choice to choice under uncertainty.

Psychological States and Preferences

Let S denote a set of *psychological states*, a list of emotions, for instance.[3] Suppose that in fact the decision maker's choices are affected by emotions, and her behavior consists in fact of a list of choice functions $C_s(\cdot)$, for any state s in S. Then a decision theorist, observing choices while varying $A \in \mathbf{A}$ but oblivious of the fact that states are also varying, might conclude the observed choice function does not satisfy the consistency requirement necessary for representation, even though consistency might instead be satisfied for each $C_s(\cdot)$. In this context, psychological states might count as primitives of the decision problem and observation of the states might represent a necessary constitutive component of a coherent revealed preferences exercise: preferences are *revealed* at the varying of the choice set A (typically through variations in prices and income) as well as at the varying of the psychological state s.

But suppose instead that, even though the decision maker's choice depends on psychological states s that are not observed in the revealed preference exercise, a representation of $C(\cdot)$ is obtained. In a certain sense, this is the showcase of the "as if" argument: no matter that choice might be related to the decision maker's psychological ~~states;~~ she chooses as if she were maximizing a well-defined preference ordering. We claim that even in this case a structural analysis of psychological states states $s \in S$ is useful to improve the explanatory power of decision theory.

To illustrate this argument, it is useful to introduce a simple formal example. Consider the typical decision problem induced by the choice of a consumption allocation $x \in \Re^n_+$ in a budget set $px \leq I$, where $p \in \Re^n_+$ is the price vector and $I \in \Re_+$ is income. The decision theorist observes a sequence of choices associated to different prices p and income I. Assuming linearity (for simplicity; our argument does not depend on this assumption) and allowing for observation errors ϵ, the decision theorist observes

$$x = \beta \begin{bmatrix} p \\ I \end{bmatrix} + \epsilon, \tag{14.1}$$

where β is a vector of unknown parameters and ϵ a random variable. The aim of the decision theorist is to explain choice (for clarity, let us say explain/predict choice), that is, x. This requires a regression analysis to estimate β.

Psychological states are summarized by a variable $s \in S$, which depends on the data of the decision problem, $\begin{bmatrix} p \\ I \end{bmatrix}$. For instance, the consumer can feel excited if his income is large (increases) or if a series of goods are sold at a bargain (a low price).[4] In summary, states satisfy

$$s = \gamma \begin{bmatrix} p \\ I \end{bmatrix} \tag{14.2}$$

(adding noise does not change the argument).

Suppose that the psychoneural process that is summarized by the variable s interacts directly (and interestingly) with choice. Suppose, for instance, that

$$\beta = \alpha s; \text{ that is, } x = \alpha\gamma \begin{bmatrix} p \\ I \end{bmatrix} + \epsilon. \tag{14.3}$$

Notice that in this formulation the decision maker's choice function has a preference representation even if the decision theorist is oblivious to states s. This manifests in the fact that the decision theorist can certainly estimate $\beta = \alpha\gamma$ without independently estimating the specific values of α and γ per se.

But, could the decision theorist improve her explanation/prediction of x by making use of her observation of s? The answer is certainly affirmative, in a statistical sense, since an independent estimate of γ can be, in general, efficiently used to improve the estimate of $\beta = \alpha\gamma$ and therefore to deepen our understanding of the relationship between the determinants of choice, $\begin{bmatrix} p \\ I \end{bmatrix}$, and choice x itself. While measurement of psychological states is not an easy task, proxies such as heart rate and galvanic skin response have been successfully employed in neuroscience (see, e.g., Damasio [1999]).

The metaphor we adopted, decision theory as a regression, is certainly a stretch, but it demonstrates effectively, in our opinion, that data on process are certainly useful as a complement to data on choice as soon as we require decision theory to provide explanation/prediction for behavior out of sample. Outside of the metaphor, structural models of the interaction between choices and psychological states could have, in principle, implications for diverse areas of decision theory, from intertemporal choice to choice under risk and uncertainty, and therefore contribute to a unifying explanation of several experimental puzzles.

The regression metaphor allows us also to stress that it is the structural model of the interaction of choice and process that really potentially adds to our abstract understanding of choice itself. Consider a formulation of the decision problem in which s is a random variable correlated with choice x, that is, with ϵ. Then, observing s would certainly reduce the noise in the prediction of x, like the introduction of any new explanatory variable in a regression will do. But it would not contribute to our analysis of choice more than the observation that "hot weather increases the demand for ice cream." We are not after adding s to as many regressions as possible; rather, we are after the structural explanation of choices. It is structural models of the determination of psychological states and emotions, as well as of their interaction with choice, which can in principle deepen our understanding of choice.

Procedural Rationality

While decision theory stands traditionally on choice axioms, an interesting literature has produced axiomatic analysis of choice processes, inspired by the work of Herbert. Simon in the 1950s (collected in Simon [1982]; see Rubinstein [1998] for a fascinating introduction to this literature).

As an illustration (we follow Rubinstein [1998] here), consider again the standard decision problem. Rather than directly postulating properties of choice (through axioms) and then deriving an "as if" representation, a theory of procedural rationality describes a choice process (a *procedure*) and then derives its implied restrictions on choice. A typical procedure is, for example, *satisficing*:

> Let O denote an ordering on $\mathbf{A}$, let T be a subset of $\mathbf{A}$, and let $A \in \mathbf{A}$ denote a choice set; then $C(A)$ contains the first element of A, according to the order O, which belongs to T (and the last element of A if A and T are disjoint).

The primitives of the procedure include T and O. The properties of the choice function $C(\cdot)$ obviously depend on a crucial manner on T and O. For instance, allowing T and O to depend on the choice set A implies that $C(\cdot)$ might not satisfy the *consistency* axiom, and that a standard representation in terms of preference maximization might not exist. The same obtains if T and O depend on psychological states $s \in S$. Behavior such as framing (the dependence of choice in experiments on the way choice problems are posed) might be rationalized by a satisficing procedure, by letting the order O depend on unobservable psychological states induced by the way choice problems are posed.[5]

A decision theory formulated in terms of a procedure such as satisficing has most explanatory power inasmuch as it includes a model of the determination of the set T and of the ordering O, for all $A \subseteq \mathbf{A}$ and psychological states $s \in S$. *Identifying choice parameters* in this context might require, then, data on process, such as those collected through the eye-tracking procedures for saccade tasks commonly adopted in vision and attention studies in neuroscience (see, e.g., Deubel and Schneider [1996]) or the mouse tracking procedure (e.g., Camerer, Johnson, Rymon, and Sen [1993]).

To better illustrate the kind of structural models we claim are useful in this context, consider the following abstract class of procedural environments:

> Let $A \in \mathbf{A}$ denote a choice set; two distinct procedures P_1 and P_2 map A into respective elements of A; a third procedure selects which of P_1 and P_2 controls choice, that is, if $C(A) = P_1(A)$ or $C(A) = P_2(A)$.

A procedure of this sort can abstractly capture a large class of cognitive decision processes that involve competing procedures and a selection mechanism. Often, the competing procedures are modeled to represent the classic automatic-controlled (or visceral/cognitive) dichotomy and the selection mechanism is represented by some form of attention control.

Procedures of this sort could represent well *choice mistakes*, "systematic phenomena which disappear once decision makers learn of their existence" [Rubinstein, 1998: 22]. A typical example is tourists looking left when crossing the street in the United Kingdom, but many other examples flood the experimental psychology literature. *Choice mistakes* provide, in fact, a useful clarifying example of the new method we delineate in this chapter. Gul and Pesendorfer (chapter 1) suggest that, according to the standard method of revealed preferences, mistakes of this sort can be rationalized simply by means of "subjective constraints on [their] feasible strategies." This is because such mistakes would be "relevant only if they could be identified through economic data." We claim instead that a structural model of the choice process leading to such mistakes would constitute a better methodological practice. It would avoid adding a "subjective constraint" every time needed, and it could provide explanatory power to understand choice in several different interesting contexts in which attention control might be relevant (see also the discussion in the next section regarding intertemporal choice).

A model of the procedures P_1 and P_2 as well as of the selection mechanism, the primitives of the procedure, is necessary to provide unifying explanations for choice mistakes. But what are the components such a model? What is *automatic*, what is *cognitive*, and what is *attention*?

While we do not know of an axiomatic analysis of this class of procedures, models of this kind of behavior have been developed, and their structural empirical implications have been studied in neuroscience. The *language* of modeling in neuroscience is different than in economics: it involves simulating the dynamic activation properties of a neuronal network rather than deriving the logical implications of axiomatic relations. Nonetheless, these models provide natural constructs for the structural analysis of choices and of choice processes.

As an illustration, consider Cohen, Dunbar, and McClelland's [1990] cognitive control model of automatic and controlled processes in the Stroop task, after the experiments by Stroop in the 1930s.[6] The Stroop task consists in naming the ink color of either a conflicting word or a nonconflicting word (e.g., respectively, saying "red" to the word "green" written in red ink, and saying "red" to the word "red" written in red ink). Cohen et al.'s [1990] model is based on *parallel distributed processing* (PDP).[7] PDP models consist of a collection of different processing units distributed over a network whose architecture represents processing modules and pathways. Each processing unit is characterized by a pattern of activation that dynamically propagates over the network, from the exogenous inputs to the output. For instance, letting the index i run over all the processing units that input into element j, the activation of j at time t, $a_j(t)$, is written as follows:

$$a_j(t) = \tau \sum_i a_i(t) w_{ij} + (1 - \tau) \sum_i a_i(t-1) w_{ij},$$

where w_{ij} represent the weight (or strength) of the connection between unit i and j.

Cohen et al. [1990] model word-reading and color-naming as competitive processing pathways in the network, which are simultaneously activated by the word image. Furthermore, a different pathway is activated by the explicit goal of the cognitive task, say, color-naming, which cognitively controls the output of the task by differentially activating the appropriate processing pathway and inhibiting the other one.

This model is crucially supplemented by a specific learning model that determines endogenously the weights of the connections w_{ij} in the network. An *automatic* pathway is defined as one that has been repeatedly active in the past, so that the learning process has generated high connecting weights, and the output is quickly generated from the input. In Cohen et al. [1990], word-reading, which is a very common task in the subjects' practice outside the lab, is modeled as an automatic process that produces a rapid response. The controlled processing aspect of the task can, however, override the stronger word-reading process by inhibiting the automatic reading association.[8]

The model implies a pattern of reaction times to conflicting and nonconflicting words that is consistent with the pattern observed in experiments with Stroop: (i) reaction times for reading tasks are unaffected by the ink color, (ii) reaction times for conflicting words are longer than for nonconflicting words, and (iii) reaction times are longer, for either conflicting and nonconflicting words, than the reaction times of simple reading tasks.[9]

While these models has been developed to understand behavior in cognitive rather than decision-theoretic tasks, we suggest that this class of models could very usefully be adapted to study choice processes. We believe that formal models of automatic and controlled processes can provide a unifying explanation of choice mistake as well as of several other puzzling choice phenomena documented in the experimental lab, in several decision-theoretic environments ranging from intertemporal choice (see the following section) to choice under uncertainty [see Loewenstein and O'Donoghue, 2005].

Intertemporal Choice: The Method in Practice

In the preceding section, we argue that models and data on psychological states and choice processes are, in principle, useful to decision theory. In this section, we survey as an illustration the literature concerning intertemporal choice. We identify in the lack of structural analysis a bottleneck of neuroeconomics in this context.

The standard economic approach to the study of intertemporal decisions involves agents maximizing their present *exponentially* discounted utility. Exponential discounting postulates that the present discounted value of a reward u received with a t-period delay is $\delta^t u$ for some $\delta < 1$.[10] Recently, however, behavioral economists have criticized this approach on the basis of a vast amount of behavioral regularities (called "anomalies") documented in experimental psychology that indicate that agents may have a preference for present consumption, a "present bias," that cannot be rationalized with exponential discounting.[11] The most important of such regularities is called "reversal of preferences." It occurs when a subject prefers $x now rather than $x + Δ in a day, but he prefers $x + Δ in a year plus a day rather than $x ~~now~~.

Various alternative decision theories have been developed that rationalize such data, and reversal of preferences in particular. For instance, Laibson [1996] and O'Donoghue and Rabin [1999] favor a quasi-hyperbolic specification of discounting, which posits that the present discounted value of a reward u received with a t-period delay is $\beta\delta^t u$ for some $\beta, \delta < 1$. Others (e.g., Ainsle [1992]) favor a hyperbolic specification, implying a discounted value of the form $(1/1 + \delta t)u$. Finally, Gul and Pesendorfer [2001] develop an axiomatic theory of temptation and self-control that rationalizes present bias by extending the domain of choice to sets of actions.

All these are standard decision-theoretic models in that they induce restrictions/implications only on choice, and not on processes, and they are formulated as a preference representation.[12] They can therefore be tested in the experimental lab with choice data.[13] As we argued in the preceding sections, however, this is not enough to conclude that data on process are not useful: data on process can, in principle, help explain choice. We next survey selectively some attempts at doing just that in practice in the context of intertemporal choice.

For instance, Wilson and Daly [2004] document higher discounting for men after having observed photographs of women that they reported as attractive. This finding can be appealingly interpreted as a manifestation of dependence of discounting on psychological states; the photographs are "inducing a 'mating opportunity,'" in the words of the authors [S177]. No model of such dependence is, however, developed that can be tested with choice or with process data. Consequently, the authors are silent on the possible relationship between psychological states and the discounting anomalies that we seek an explanation for.[14]

Much more important and central to our understanding of the interaction between choice and process are two recent studies at the forefront of neuroeconomics, McClure, Laibson, Loewenstein, and Cohen [2004] and Glimcher, Kable, and Louie [2006]. ~~who develop and study brain imaging data to explicitly distinguish between some of the different preference representations.~~

Both McClure et al. [2004] and Glimcher et al. [2006] produce and study brain imaging data ~~during~~ intertemporal choice tasks. ~~They then interpret these data as evidence in favor of different preference representations of discounting that rationalize present bias anomalies.~~ In particular, McClure et al. [2004] claim evidence for the quasi-hyperbolic representation of discounting. They postulate that such representation results from the influence of two distinct neural processes, one that is differentially activated in the presence of immediate rewards, and one that is commonly activated when the decision maker engages in intertemporal choices. They then measure brain activation of several subjects in an intertemporal choice task by functional magnetic imaging (fMRI) techniques and identify econometrically areas of differential activation when the choice task involves an immediate reward. McClure et al. [2004] then categorize such areas of the brain as β-*areas*, interpreting them as representing present bias, and more generally interpret the existence of such areas as evidence in favor of the existence of two neural processes involved in intertemporal choice.

McClure et al. [2004] provide no structural analysis of choice and process underlying the different neural processes. No choice data are reported. No formal model of the neural processes that are postulated to underlie choice is proposed, and hence, no formal implications are derived regarding the pattern of activation of different areas of the brain. Furthermore, no clear a priori theoretical presumption links quasi-hyperbolic discounting with two distinct neural processes.[15] As a consequence, the empirical results of McClure et al. [2004] are prone to different interpretations and can hardly identify the properties of the underlying choice process that they observe in their fMRI study, including the existence of two neural processes involved in intertemporal choice. In this sense, Glimcher et al. [2006] argue that the activation patterns found in McClure et al. [2004] are, in fact, consistent with the hypothesis that brain activation simply correlates with an hyperbolic representation of the decision maker's discounting preferences, the implicit choice process in this case simply being represented by discounted utility maximization (without recourse to two neural processes).

Glimcher et al. [2006] ~~proceed then to~~ estimate discounting preferences with choice data, finding that a hyperbolic representation is not statistically rejected. They measure~~d~~ brain activation by fMRI and f~~ound~~ a clear correlation pattern of activation measurements in areas of the brain typically associated with option valuation with the discounting representation estimated with choice data. This is interpreted as evidence for an explicit preference maximization procedure underlying intertemporal choice. Lacking a structural model of choice and process, however, the data can once again hardly identify the (single or multiple) neural processes involved in intertemporal choice.

In summary, the neuroeconomics literature has made great progress in studying brain imaging data of decision makers engaged in intertemporal choice tasks. Structural models to guide the empirical analysis are still lacking, however, that can provide the decision theorist with the explanatory power to distinguish between different choice representations of discounting and hence, ultimately, to explain intertemporal choice anomalies.

In the quest to explain intertemporal choice anomalies, a few models of choice and process have been developed and studied. Unfortunately, until now these models have been studied empirically only with choice data from the experimental lab and not yet with data on process itself. We illustrate this point by explicitly discussing two such models, Rubinstein [2003] and Benhabib and Bisin [2004].

Rubinstein [2003] considers a simple procedural model of the binary choice over rewards x at different delays t. The procedure studied is a *similarity* procedure:[16] facing the binary choice over (x, t) and (x', t'), the decision maker first looks for dominance, for example, choosing (x, t) if $x \geq x'$ and $t \geq t'$ (with at least one strict inequality); lacking dominance, the decision maker looks for *similarity*, for example, choosing (x, t) if x *is similar to* x' and $t > t'$; if the two previous procedures are inconclusive, choice is made using yet another procedure.

Several choice experiments are designed that can distinguish hyperbolic discounting from the similarity procedure (once complemented with a specific notion of the relation *is similar to*) and choice data are provided that support the similarity procedure.

Note also that, in accordance with the methodological claim we are exposing, that is, that models of process have the potential of providing unifying explanation of various phenomena in experimental choice behavior, a related similarity procedure has been studied by Rubinstein [1998] in the context of choice over risky lotteries. While rich implications of the similarity procedure can certainly be derived on process data (e.g., on reaction times), we know of no research along these lines.[17]

Benhabib and Bisin [2004] provide instead an intertemporal choice model in which choice is the result of the interaction of automatic and controlled processing.[18] When specialized to the binary choice over rewards at different delays, the typical choice experiment that gives rise to the *anomalies* in experiments, Benhabib and Bisin's [2004] model induces a present discounting representation of a reward u at delay t of the form $\delta^t u - b$, where b represents the psychological cost induced by the need to exercise self-control, interpreted as a psychological restraint from the impulse of choosing the immediate reward. The cost of delay b is a fixed cost, that is, is independent both of the size of the reward and of the amount of the delay.[19] Benhabib, Bisin, and Schotter [2005] estimated discount preferences with experimental choice data and found statistical evidence that in fact favors this representation over both quasi-hyperbolic and hyperbolic discounting.

A different test of Benhabib and Bisin's [2004] model can be performed, once again, with experimental choice data, by considering a simple environment in which an agent has to decide how much to consume today out of available income z. When their analysis is specialized to this simple environment, they obtain the following representation:

$$\max \left\{ \max_{x \leq z} \; u(x) - b, u\left(\arg\max_{x \leq z} v(x)\right)\right\}, \tag{14.4}$$

where $u(x)$ and $v(x)$ are smooth, concave real functions representing, respectively, the cognitive and automatic components of preferences. The cognitive component of preferences controls choice if and only if its valuation minus the self-control cost b is larger than the automatic valuation $u\left(\arg\max_{x\leq z} v(x)\right)$. Under some regularity assumption,[20] this representation has the identifying behavioral implication: the choice $x(z)$ is not increasing in z, but rather has a decreasing jump; small temptations are not controlled, while large ones are.

In work in progress, Benhabib, Bisin, and Kariv are exploring this implication in the experimental lab. About a half of the 20 subjects for which data have been collected display the behavior predicted by the model.

While Benhabib and Bisin's [2004] model of intertemporal choice and process has been tested with choice data, as we reported above, the model also has potentially several clear-cut implications about process that can be derived by formulating a parallel distributing processing model along the lines of the Stroop model in Cohen, Dunbar, and McClelland [1990] and that can be tested, for example, by recording reaction times data during an intertemporal choice task. This has not yet been done.

The theory of intertemporal choice is a fascinating laboratory: it has (i) choice *anomalies* to explain; (ii) sophisticated models, from axiomatic to algorithmic, to put to data; and (iii) a wealth of data, from the experimental choice data to brain imaging data, to test its models. All the ingredients for the application of the new method we have discussed are ready to be mixed.

While intertemporal decision theory appears representative of other areas of neuroeconomics in terms of the methods used, structural models of choice and process are being developed at the frontier, for instance, in the study of reward prediction errors in learning [Caplin and Dean, 2007] and in the study of random utility [Maccheroni, Marinacci and Rustichini, 2006].

Conclusions

In this chapter we have argued that, in our opinion, no logical reasons exist to exclude models and data on choice processes from decision theory. On the contrary, the structural analysis of models and data on process represents, in our opinion, the fascinating frontier of decision theory.

While standard decision theory has been very successful in rationalizing a rich set of behavioral data from lab experiments by a combination of weakening of the axioms and enlarging of the choice set,[21] it seems to us that this success has come at the expense of explanatory power, that is, of a unified theory of decision making. A new method exploiting the study of choice processes as well as choices, in our opinion, contains the promise of unifying the explanations of many behavioral puzzles observed in the experiments.

With respect specifically to the theory of intertemporal choice, we have noted that the structural analysis of choice and process that we claim could advance our understanding of choice seems to be yet missing: the most advanced brain imaging techniques are adopted without the guide of theoretical analysis, resembling what economists call "fishing for factors," while the few models that in fact focus on the interaction of choice and process are tested only with choice data, wasting much of their explanatory/predictive power.

We conclude this chapter by claiming an added rhetorical advantage for a methodology for decision theory that goes beyond "as if" representations by directly formulating models of choice processes can be tested with data on process. The representation of preferences in the standard theory of revealed preferences is often, by its very nature, an informal description of a process. The elegance of the representation, its accordance with introspective beliefs about decision processes *inspire* it[22]—in summary, its *intuitive appeal*—is typically crucial for a decision theory to be accepted. The necessarily informal (but important) role that such concepts as *intuitive appeal* or *inspiration* end up performing in the method of revealed preferences is in our view a substantial limitation of the method itself. Wouldn't it be much better to lay all the cards down for inspection?

NOTES

Many of the ideas exposed in this chapter evolved in the course of discussions with Aldo Rustichini, who appeared as co-author in previous versions of the paper. Thanks to Andrew Caplin, Chris Flinn, Ariel Rubinstein, and Yuval Salant for useful discussions.

1. Intellectual interest in the study of decision processes can, however, be traced to the classic period, from W. S. Jevons's "Brief Account," [1866] or chapters II and III of his *Theory* [1871], to J. Bentham's *Principle's of Morals and Legislation* [1780], or to A. Smith's *Theory of Moral Sentiments* [1759].

2. The classic formulation of the methodology of structural empirical analysis is in Koopmans [1947] and Marschak [1952]. A recent discussion is contained in Keane [2006].

3. See Kahneman and Krueger [2006] for a survey of the theoretical constructs and the measurement issues behind the notion of psychological states.

~~4. Evidence is collected through skin conductance measurement.~~

5. Relatedly, see Rubinstein and Salant [2006] for the axiomatic treatment of choices from lists.

6. The distinction between automatic and controlled processing is common in neuroscience and is articulated, e.g., in Schneider and Shiffrin [1977] and in Norman and Shallice [1980].

7. See Rumelhart and McClelland [1986] for an extensive presentation and discussion of PDP models in neuroscience.

8. See Miller and Cohen [2001] for a general introduction to attention control models and their structural empirical analysis.

9. Furthermore, patients with frontal impairment have difficulties with the Stroop task; see Cohen and Servan-Schreiber [1992] and Vendrell et al. [1995].

10. See Koopmans [1960] and Fishburn and Rubinstein [1982] for the classic axiomatic treatment of intertemporal choice.

11. See, e.g., Ainsle [1992] and Frederick, Loewensteinm, and O'Donoghue [2002] for comprehensive surveys.

12. See Ok and Masatlioglu [2006] for general axiomatic representations of these discounting preferences.

13. This is done, e.g., by Benhabib, Bisin, and Schotter [2005].

14. See Smith and Dickhaut [2004] for empirical evidence on the effect of emotions on bidding in auctions.

15. Intuitively, however, the power of the test relies on their finding that β-*areas* are mostly located in the limbic system, which is an area of the brain typically associated with impulsive choice rather than cognitive processing.

16. See Tversky [1977] for the early introduction of similarity relations in decision making.

17. But see Rubinstein [2007], which relates cognition and reaction times in several strategic environments.

18. While Benhabib and Bisin [2004] model the choice process directly, without providing its axiomatic foundation, see Nehring [2006].

19. Note that the quasi-hyperbolic representation can be written $\delta^t u - (1-\beta)\delta^t u$ ~~and hence implies~~ instead a variable cost associated to nonimmediate rewards, that is, a cost proportional to the value of the reward u.

20. In particular, assuming

$$x^* = \arg\max_{x\in X}\ u(x) < \arg\max_{x\in X}\ v(x)$$

allows the interpretation, essentially without loss of generality, of "temptations" as "preferences for a larger ~~x," so~~ z measures, parametrically, the "size" of the temptation.

21. Notable examples include Kreps and Porteus [1978] on early resolution of uncertainty, Gilboa and Schmeidler [1989] on uncertainty aversion, Gul and Pesendorfer [2001] on present bias, among many others.

22. In this sense, Gul and Pesendorfer (chapter 1) accept a reference to process in decision theory as *inspiration*.

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