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Economic Insights from "Neuroeconomic" Data

By Andrew Caplin and Mark Dean*

How and to what extent "neuroeconomic" data (broadly interpreted as data other than standard choice data) should be used in advancing economic theory is open to question. Several authors have attempted to make use of such nonstandard data to shed light on the process of economic decision making. John W. Payne, James R. Bettman, and Eric. J. Johnson (1993), Miguel Costa Gomes, Vincent P. Crawford, and Bruno Broseta (2001), and Xavier Gabaix et al. (2006) have used MouseLab software in order to determine the manner in which people use information. Joseph Wang, Michael Spezio, and Colin Camerer (2006) make use of eye-tracking data for the same purpose. More dramatically, researchers such as Paul William Glimcher, Joseph Kable, and Kenway Louie (2007) are using brain-scanning data in an attempt to constrain economic models of discounting and time preference. Camerer (forthcoming) presents an excellent review of economic research involving nonstandard data.

In opposition to this trend, Faruk Gul and Wolfgang Pesendorfer (forthcoming) present a strong critique of the use of nonchoice data within economics. They put forward two specific arguments that users of "neuroeconomic" data must refute if their work is to be taken seriously. First—economic models were designed only to explain choices. Thus, nonchoice data can be used neither to confirm nor deny a particular economic model. Second, it is by and large true that economists are interested in choice behavior. Any two models will either make different predictions for choice, in which case they can be differentiated by standard choice data, or they will not, in which case an economist will not be interested in differentiating between them.

It is our view that there is a role for nonstandard choice data in helping us understand economic decision making.[1] However, we see the Gul and Pesendorfer critiques as forming a crucial "litmus test" against which the value of such research should be judged. With regard to the first criticism, it is not sufficient for a researcher to simply use nonstandard observations to comment on standard economic models in an ad hoc way. Rather, new theoretical models that explicitly incorporate these new data must be developed. The second criticism, while oversimplifying the task of characterizing economic behavior, does highlight the role of the researcher in explaining what their nonstandard data are *for*. Rather than simply deciding between two models, an economist who is interested in behavior is faced with a bewilderingly large array of possible models to choose among, and an equally large range of environments in which these models may or may not be applicable. Nonstandard data can be an efficient way of directing search within this space, by allowing the researcher to model distinct parts of the decision-making process which are usually aggregated in choice. Moreover, identifying the "microfoundations" of decision theory in the processes which underlie choice can potentially lead to more robust models of decision making, just as occurred with the microfoundation of macroeconomics.[2] It is with these goals in mind that the value of nonstandard data should be judged.

In this paper, we illustrate our position with two specific examples. First, we consider the role of information search in choice. The standard model of economic choice has no explicit description of how a decision maker searches through a choice set for information on the available alternatives. In fact, we show that standard choice data cannot be used to examine

* Caplin: Department of Economics, New York University, 19 West 4th Street, New York, NY 10012 (e-mail: andrew.caplin@nyu.edu); Dean: Department of Economics, 19 West 4th Street, New York, NY 10012 (e-mail: mark.dean@nyu.edu). We thank Paul Glimcher and Drew Fudenberg for insightful suggestions. We also thank the National Science Foundation and the C. V. Starr Center at NYU for research support.

[1] The arguments made here are discussed in more detail in Caplin (forthcoming).

[2] A similar point on the potential value of neuroeconomic data is made by Drew Fudenberg (2006).

the process of information search explicitly: any choice data can be rationalized by a simple model of optimal information search. We therefore introduce new data that allow us to model the search process. The resulting model can generate behavior such as random choice, framing effects, and status quo bias, even for a decision maker (DM) with fixed preferences.

Our second example examines the role of the neurotransmitter dopamine. Many neuroscientists have claimed that dopamine has a role in calculating the *reward prediction error* (RPE) of a particular event, or the difference between how good the event is, and how good it was expected to be. We use tools standard to decision theory to characterize this hypothesis, and therefore produce testable implications. We then discuss the potential of this model to provide insight into choice, belief formation, and learning.[3]

I. Revealed Preference, Search, and Choice

Our first foray into the world of nonstandard data is spurred by our desire to examine the process by which DMs search through various alternatives in a choice set. We consider a model in which DMs search sequentially through available objects until some stopping rule is triggered, at which point they choose the best object available according to a fixed utility ranking. Unfortunately, if search is invisible, any standard choice data are rationalizable with such a model. For example, if x is chosen over y in one choice set, while y is chosen over x in another, it may be simply that the DM was not aware of the existence of x in the second choice set. Thus, standard choice data cannot be used to test such models of search.

In order to resolve this identification problem, we introduce the concept of "choice process" data that records not only the choice that a decision maker ultimately makes, but also how the chosen option evolves over the pre-decision period. In our data, the decision maker is observed selecting at each discrete time $t \in \mathbb{N}$ a subset of the choice set. The interpretation is that this selection represents what the DM would choose if they had considered the choice problem for this length of time. The choice process model comprises the entire set of such observations for different values of the time index and for all nonempty subsets of the choice set.[4]

DEFINITION 1: *Let $\mathcal{X}$ be all nonempty subsets of a finite set X: $\mathcal{X} = 2^X/\phi$. Given $A \in \mathcal{X}$, a* ***choice process from*** *A is a function $C: A \times \mathbb{N} \to \mathcal{X}$ with $C(A,t) \subseteq A$: the class of all such choice processes from A is denoted $\mathcal{C}^A$, with the union over $\mathcal{X}$ of all such sets $\mathcal{C}^A$ being denoted $\mathcal{C}^{\mathcal{X}}$. A choice process model comprises the underlying set X and a* ***choice process*** *(from X), $\mathcal{C} : \mathcal{X} \to \mathcal{C}^{\mathcal{X}}$, with $\mathcal{C}(A) \in \mathcal{C}^A$ all $A \in \mathcal{X}$.*

CDA formulate a simple theory of "alternative based search" (ABS) in which the decision maker searches through the choice set sequentially, at any time choosing the most preferred object yet encountered.

DEFINITION 2: *A choice process model (X, C) permits an alternative-based search* ***(ABS)*** *representation (u, S) if there exists a utility function $u : X \to \mathbb{R}$ and a correspondence $S : \mathcal{X} \times \mathbb{N} \to \mathcal{X}$, the* ***search process****, that is, expanding (i.e., $S(A,s) \subseteq S(A,t) \subseteq A$ for all $A \in \mathcal{X}$ and $t \geq s$) and such that,*

$$C(A,t) = \arg\max_{x \in S(A,t)} u(x).$$

While we do not, by any means, consider ABS a universal description of search behavior, it does present a parsimonious benchmark model with which to start a discussion of information search. Moreover, such a simple model can generate a number of well-studied documented anomalies.

Any standard choice function is commensurate with the ABS model: it is only for our expanded dataset that the ABS model has any empirical traction. The precise characterization of these restrictions rests on an understanding of what is meant by "revealed preferred" within the context of the ABS model and choice process data. This information is summarized in

[3] The first of these examples is explored fully in Caplin and Dean (2008) (henceforth CDA), while the second comes from Caplin and Dean (forthcoming) (henceforth (CDB) and Caplin, Mark Dean, Glimcher, and Robb Rutledge (2008) (henceforth CDGR).

[4] A similar dataset is considered in Donald Campbell (1978).

the binary relations $\succ^{\mathcal{C}}$ and $\sim$ introduced below. Intuitively, x is revealed preferred to y if it is chosen after y in some choice process, as this implies that x is chosen over y when the DM knows that y is available.

DEFINITION 3: *Given a choice process model* (X, C), *the symmetric binary relation* $\sim$ *on* X *is defined by* $x \sim y$ *if there exists* $A \in \mathcal{X}$ *and* $t \in \mathbb{N}$ *such that* $x, y \in C(A,t)$. *The binary relation* $\succ^{\mathcal{C}}$ *on* X *is defined by* $x \succ^{\mathcal{C}} y$ *if there exists* $A \in \mathcal{X}$ *and* $t \in \mathbb{N}$ *such that* $x \in C(A,t)$, $y \notin C(A,t)$, *but* $y \in C(A,s)$ *for some* $s < t$. *The binary relation* $\succsim^{\mathcal{C}}$ *on* X *is defined as* $\succ^{\mathcal{C}} \cup \sim$.

The key to being able to find an ABS representation is for the information embodied in $\succsim^{\mathcal{C}}$ to be consistent. By this we mean that we can find a utility function $u : X \to \mathbb{R}$ such that $x \succ^{\mathcal{C}} y \Rightarrow u(x) > u(y)$ and $x \sim y \Rightarrow u(x) = u(y)$. It turns out that the necessary condition is a variant of acylicality.

AXIOM A1 (*Weak* $\succsim^{\mathcal{C}}$ *Cycles Only*): *Given* $x_1, x_2, x_3, \ldots, x_n \in X$ with $x = x_1 \succsim^{\mathcal{C}} x_2 \succsim^{\mathcal{C}} x_3 \ldots \succsim^{\mathcal{C}} x_n = x$, *there is no* k *with* $x_k \succ^{\mathcal{C}} x_{k+1}$.

A1 is both necessary and sufficient for an ABS representation.[5]

THEOREM 1: *A choice process model* (X, C) *allows an ABS representation if and only if it satisfies* A1.

The ABS model is silent concerning how and why search is terminated. One way to refine the model is to augment it with some form of stopping rule. A particularly simple rule is based on a "reservation utility" strategy—search continues until an object is found which has utility above a certain level. If no such object is found, search continues until all objects have been examined. In technical terms, a reservation-based search (RBS) representation of a choice process model consists of an ABS representation together with a reservation level of utility. For sets in which there are no objects above the reservation level, we demand that the limit search correspondence be the whole set. By the same token, if there are objects in the set that are satisfactory in this sense, search must continue until one of them is found. Finally, once an object is found with a utility above the reservation level, search stops.

DEFINITION 4: *A choice process model* (X, C) *admits of a reservation-based search* (***RBS***) *representation* (u, S, u^*) *if it permits an ABS representation* (u, S) *with the property that, given* $A \in \mathcal{X}$:

(i) $\max_{\{x \in A\}} u(x) < u^* \Rightarrow \lim_{t \to \infty} S(A,t) = A$;

(ii) $\max_{\{x \in A\}} u(x) \geq u^* \Rightarrow \exists t$ *such that, for some* x *with* $u(x) \geq u^*$, $x \in S(A,t)$;

(iii) *If* $\exists x \in S(A,t)$ *with* $u(x) \geq u^*$, *then* $S(A,s) = S(A,t)$ *for all* $s > t$.

While we do not formally characterize the RBS model here (see CDA for details), we can describe the characterization informally. In the context of RBS, the concept of "revealed preferred" is extended. If x is chosen from a choice set containing only items of below reservation utility, then it must be the case that x is preferred to all the other objects in the choice set. A RBS representation requires all such preference information to be consistent, in the sense described above.

The RBS model is similar to the satisficing model of Herbert Simon (1955). We show also in CDA that the reservation strategy can be seen as optimal behavior for a decision maker with fixed search cost, specified in utility terms.

A final extension to consider is the case in which search order is itself a random variable from the point of view of the observer or experimenter: the order of search is, in general, invisible to the outside observer, and so it is quite possible that it may change from experiment to experiment without the experimenter knowing. In such a case, a decision maker facing the *same* choice set on multiple occasions could make very different choices, due to variations in search order. In CDA we formalize stochastic versions of choice process data and the ABS and RBS models.

While it is clearly true that choice process data are necessary in order to model search, it could be argued that the resulting models are of little use to economists, as they have little to say about final choice. We can show, however, that our simple information search model can

[5] For all proofs, as well as further detail, see CDA.

generate many well-documented behavioral anomalies, even with a decision maker who has consistent preferences. These include:

- *Random Choice:* Many experimental results (for example Glimcher, Kable, and Louie 2007) show that choices within an individual are not consistent: different choices can be made from the same choice set on different occasions. While this is generally modelled using a random utility model, in which preferences vary stochastically, we show that it can equally well be modelled via search orders that vary stochastically, while preferences are fixed.
- *Framing Effects:* Many experiments have shown that choices can be affected by seemingly extraneous presentation choices—for example, the order in which options are presented on a screen. Again, this can be modelled as being due to variations in search order affecting the choices of a DM with a fixed utility function.
- *Status Quo Bias:* One particular class of framing effect is status quo bias, which describes a situation in which an object is more likely to be chosen simply because it is the status quo point. Within the RBS model, this can be modelled as the presence of a status quo point altering the search order, and increasing the probability that the status quo object will be searched early, and therefore chosen.

Our search model, therefore, provides an alternative explanation for various behavioral anomalies, and choice process data offer a way to test these theories. The fact that different explanations cannot be differentiated using standard data was first pointed out by H. D. Block and Jacob Marschak (1960) in an article in which they also suggest using enriched data in order to determine whether stochastic choice is driven by changes in search order or preferences. Choice process data allow us, in principle, to make such a differentiation, and so help guide further theoretical and empirical research in this area.

It is eminently plausible that experimental techniques can yield information on the choice process. Together with Daniel Martin, we are developing at NYU experimental methods to gather information on the choice process. The idea of the design is to allow subjects to highlight their most preferred lottery at any time by clicking on it. They are allowed to change this selection as frequently as they wish. While subjects will be given a fixed upper time limit within which to examine the set and highlight whichever lottery they wish, they will be aware that their *choice* will be recorded at some randomly determined, unannounced time within this interval. The goal of introducing this uncertainty is to incentivize subjects to highlight whichever option they feel is best at any given time: if they do not, the currently highlighted option may be recorded as their "choice," even though they would, in fact, prefer a different choice. This makes it plausible to interpret the resulting sequence of selected lotteries as an observation of the choice process for that choice set.

II. Dopamine and Reward Prediction Error

One might argue with our designation of choice process data as neuroeconomic. Not so for our second area of research, in which the data that we add are purely neuroscientific. We formalize the idea (discussed in detail in CDB) that the neurotransmitter dopamine records a *reward prediction error*—the difference between how good an event is and how good it was expected to be. It takes little imagination to see how interesting information of this form might be for our understanding of beliefs, reward, and choice behavior. In addition, B. Douglas Bernheim and Antonio Rangel (2004) point out the growing consensus that dopaminergically mediated learning is implicated in addictive behavior. Moreover, many authors (for example, Wolfram Schultz, Peter Dayan, and P. Read Montague 1997) have shown that such a reward prediction error signal is a key algorithmic component of the reinforcement learning model. They have therefore suggested that dopamine may play a crucial role in learning.

CDB took the steps necessary to translate the Dopaminergic Reward Prediction Error (DRPE) hypothesis from the neuroscientific to a simple economic setting in which prizes are received from lotteries. We are now in the process of developing appropriate neuroscientific tests (see CDGR). The version of the model that we are currently testing is based on a finite set of observations of dopamine release when prizes are obtained from a small set of simple lotteries. The key observable is the firing rate of dopamine neurons, $\delta(z,p)$, resulting from a prize z being received from some lottery p.

DEFINITION 5: *A **finite dopaminergic data** set (DDS) comprises a tuple (Z, A, δ), with Z a set of prizes, A a finite set of **prize-lottery pairs** (z,p), with $z \in Z$ and p a probability distribution over Z with $z \in Supp(p)$ and $\delta : A \to \mathbb{R}$ specifies the **dopaminergic firing rate** for each observation $(z_n, p_n) \in A$.*

Defining $\Lambda^A \equiv \cup_{(z_n,p_n)\in A} p_n$, the definition of a DRPE representation has three parts. First, there must be a "reward" function $r : \Lambda^A \to \mathbb{R}$ that is a sufficient statistic for recording the dopaminergic response to any given lottery-outcome pair:

$$\delta(z,p) = E(r(z), r(p)).$$

Second, defining $r(Z)$ and $r(\Lambda^A)$ as the ranges of the reward function on the respective domains, there must be a larger dopaminergic response to a more rewarding outcome and/or less rewarding prior anticipations: given (a,b), $(a',b') \in r(Z) \times r(\Lambda^A)$,

$$a' > a \Rightarrow E(a',b) > E(a,b);$$

$$b' < b \Rightarrow E(a,b') > E(a,b).$$

Finally, all situations in which the actual outcome was perfectly anticipated must be dopaminergically equivalent: given $z, z' \in Z$,

$$E(r(z), r(z)) = E(r(z'), r(z')).$$

CDGR outline three necessary conditions for a DRPE: that all situations of no surprise are equivalent; that prizes are coherently ordered by dopamine; and that lotteries are also so ordered. When there are three or more prizes, these conditions are necessary but not sufficient for a DRPE representation. Yet in the two-prize case, one can provide directly that such equivalence does indeed hold.

THEOREM 2: *With two pure prizes, a finite DDS admits a DRPE if and only if $\delta(z',z') = \delta(z,z)$ all $z, z' \in Z$, and, given (z,p) (z',p), (z,p'), $(z',p') \in A$,*

$$\delta(z,p) > \delta(z',p) \Rightarrow \delta(z,p') > \delta(z',p');$$

$$\delta(z,p) > \delta(z,p') \Rightarrow \delta(z',p) > \delta(z',p').$$

We are currently in the process of using this formalization to organize the collection of data to allow us to test this hypothesis. This involves endowing subjects with lotteries, then realizing these lotteries while the subjects are within a functional magnetic resonance imaging (fMRI) machine. By using the fMRI machine to collect data on brain activity in regions with many dopamine neurons, we can test these hypotheses directly.

Again, while this is of great interest to neuroscientists, what use is it to economists? We argue that validity of the DRPE hypothesis, and the related hypothesis concerning the role of dopamine in learning, would open the door to fundamental economic insights:

- *Dopamine and the construction of utility:* According to the DRPE hypothesis, dopamine contains information on "reward," which in turn acts as an input into choice. As such, we can see dopamine as a key input into the construction of "utility," or a building block in determining the choices people make.
- *Dopamine as a carrier of information on expectations:* The DRPE hypothesis states that dopamine responds to the difference between experienced and anticipated rewards. As such, it should be possible to use observation of dopamine to back out a measure of what was expected in different circumstances, opening a new window into decision making under uncertainty and in game theoretic settings.
- *Dopamine as a building block for learning.* The importance of learning theory in economics is apparent from the effort that has been dedicated to it both within macroeconomic theory (e.g., Albert Marcet and Thomas Sargent 1989) and microeconomic theory (e.g., Fudenberg and David Levine 1998). The DPRE hypothesis suggests that dopamine forms one of the building blocks of learning within the brain. Understanding the DRPE can therefore be thought of as the first step in developing a "neuroeconomic theory of learning."

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