Enhanced Choice Experiments*

Andrew Caplin† and Mark Dean‡

February 10, 2010

Abstract

We outline experiments that improve our understanding of decision making by analyzing behavior in the period of contemplation that preceeds commitment to a final choice. The experiments are based on axiomatic models of the decision making process that relate closely to revealed preference logic. To test the models, we artificially incentivize particular choices to be made in the pre-decision period. We show how the resulting experiments can improve our understanding not only of the decision making process, but of the decision itself. Our broad method is to make aspects of search visible while retaining the disciplined approach to data that axiomatic modeling best provides.

Key Words: Revealed preference, search, incomplete information, revealed preference, framing effects, status quo bias, bounded rationality, stochastic choice, decision time

<1>Introduction

Experiments that record more than standard choice data can improve our understanding of choice itself. In this chapter, we illustrate the advantage of such "enhanced" choice data with an example. We describe an experiment which, in addition to recording the final decision made by subjects, incentivizes choices that are made in the prior period of contemplation. We show how the

*We thank Daniel Martin for his collaboration on the research reported herein, and Marina Agranov, Sen Geng, and Chloe Tergiman for their interest in and contributions to the broader research agenda. We thank Martin Dufwenberg and the participants in the CESS Conference on Methods of Experimental Economics for valuable suggestions.

†Center for Experimental Social Science and Department of Economics, New York University. Email andrew.caplin@nyu.edu

‡Department of Economics Brown University. Email mark_dean@brown.edu

resulting data provides insight into how people search for information on the alternatives available to them. This in turn improves our understanding of the decision making process and its final outcome, which stands alone as the subject of interest in standard choice experiments.

This experiment forms part of an ongoing research project in which we aim to enrich the modeling of search behavior while retaining the theoretical discipline inherent in the revealed preference approach to choice behavior. We outline in some detail the poster child for our approach detailed in Caplin and Dean [2009] and Caplin, Dean, and Martin [2009], henceforth CD and CDM respectively. CD introduce "choice process" data, which measures not only the final option that a decision maker (DM) selects, but also how their choice changes with contemplation time before a final decision is made. CDM describe the results of an experiment designed to elicit choice process data in the laboratory.

We first describe how choice process data can be used to test models of information search and choice. CD characterize a model of sequential, or "alternative based search" (ABS), in which a DM searches through alternatives sequentially, at any time choosing the best of those they have searched according to a fixed utility function. Such behavior is standard within economic models of price and wage search. While the ABS model is silent as when people stop searching, CD provide a refinement that describes a DM who searches until an object is identified with utility above a fixed reservation level, as in the satisficing model of Simon [1955]. We call this refinement 'reservation based search' (RBS). This form of search is optimal in simple models of sequential search with psychic search costs. Importantly, neither the ABS or RBS model provide testable implications for standard choice data, meaning that choice process data is crucial in any such test.

Next, we describe a set of experiments reported in CDM designed to evaluate the ABS and RBS models. In order to simplify these tests, CDM specialize to the case of known preferences by making the objects of choice particularly simple: amounts of money. In order to prevent the choice problem from becoming trivial, these amounts are expressed in algebraic from (e.g. seven plus three minus two) and are therefore difficult to decode. While the experimenter always knows which of these numerical expressions is largest and therefore most preferred, the DM must work to assess each alternative. In this environment it is easy to identify choice "mistakes," or cases in which a subject has failed to choose the best alternative in a choice set.

In order to test the ABS and RBS models, our experiment elicits choice process data. We obtain such data using an experimental design in which subjects' choices are recorded at a random point in time unknown to them, incentivizing them to always report their currently preferred alternative. We therefore gather information on the sequence of choice switches in the pre-decision period, which we interpret as choice process data. This represents a choice-based experiment constructed precisely to enrich our understanding of search behavior and imperfect information.

There are three key findings:

1. There is evidence in favor of the ABS model. Specifically, the vast majority of switches are in the direction of improvement, suggesting that chosen objects have been accurately assessed.

2. There is strong evidence in favor of the satisficing model. Many decision makers engage in sequential search that stops once a satisfactory level of reservation utility is achieved. These reservation levels are environmentally determined - changing with the size of the choice set and the complexity of each alternative.

3. There are interesting individual differences in search behavior that intermediate the impact of search order on choice. For example, those who tend to search lists from top to bottom fail to choose the best option if it is far down the list, while those who search less complex options first miss the best option if it is complex, even if it is high on the list.

Section 4 shows that the choice process data is essential for making inferences concerning the decision making process and its impact on choice. When we re-run the same experiments gathering information only on final choices, little can be inferred about the forces that underlie mistakes, and the empirical regularities that are uncovered by exploring the choice process get obscured. It is not possible to test the ABS and RBS models, or extract data on reservation levels.

Section 5 comments on the underlying motivation for our research and the broader methodology. We are far from the first to design experiments to study behavior in the pre-decision period. What defines our approach is the focus on choice-based enhancements that can be incentivized in an experimental laboratory. We believe that the axiomatic approach of standard choice theory provides the most robust foundation for understanding decisions. In this sense, the work described herein fits with a broader research agenda of introducing "non-standard" data yet retaining the modeling discipline that axiomatic modeling provides. Caplin and Dean [2008] and Caplin, Dean, Glimcher, and Rutledge [2010] outline a distinct application of this approach that jointly characterizes standard choice data and neuroscientific data on the dopamine system.

The concluding remarks in section 6 outline immediate next steps in the agenda. In the longer run, we see research on the relationship between search and choice as of ever increasing importance in the age of Google and of policy “nudges.“ How we learn and choose when complex options are presented in various different manners is a question that will be increasingly under the microscope in the years to come, and on which research of the form outlined herein may shed light.

<1>Choice Process Data: Theory

Choice process data is designed to provide insight into search-based causes of mistakes. Rather than recording only the final decision, these data track how the choices that people make evolve with contemplation time. As such, choice process data comes in the form of sequences of observed sets of choices from any given set of options rather than comprising a single set of chosen options (the theory allows for indifference and therefore simultaneous selection of several elements from a set). To formalize, let X be a nonempty finite set of elements representing possible alternatives, with $\mathcal{X}$ denoting non-empty subsets of X. Let $\mathcal{Z}$ be the set of all infinite sequences from $\mathcal{X}$ with generic element $Z = \{Z_t\}_1^\infty$ with $Z_t \in \mathcal{X}/\emptyset$ all $t \geq 1$. For $A \in \mathcal{X}$, define $Z \in \mathcal{Z}_A \subset \mathcal{Z}$ if and only if $Z_t \subset A$ all $t \geq 1$.

Definition 1 *A* ***choice process*** (X, C) *comprises a finite set* X *and a function,* $C : \mathcal{X} \to \mathcal{Z}$ *such that* $C(A) \in \mathcal{Z}_A \ \forall \ A \in \mathcal{X}$.

Given $A \in \mathcal{X}$, choice process data assigns not just final choices (a subset of A), but a sequence of such choices, representing the DM's choices after considering the problem for different lengths of time. We let C_A denote $C(A)$ and $C_A(t) \in A$ denote the t-th element in the sequence C_A, with $C_A(t)$ referring to the objects chosen after contemplating A for t periods. Choice process data represents a relatively small departure from standard choice data, in the sense that all observations represent choices, albeit constrained by time.

The first model CD analyze captures the process of sequential search with recall, in which the DM evaluates over time an ever-expanding set of objects, choosing at all times the best objects thus far identified. Choice process data has an alternative-based search (ABS) representation if there exists a utility function and a non-decreasing search correspondence for each choice set such that what is chosen at any time is utility-maximizing in the corresponding searched set.

Definition 2 *Choice process (X, C) has an* ***ABS*** *representation (u, S) if there exists a utility function $u : X \to \mathbb{R}$ and a search correspondence $S : \mathcal{X} \to \mathcal{Z}^{ND}$, with $S_A \in \mathcal{Z}_A$ all $A \in \mathcal{X}$, such that,*

$$C_A(t) = \arg\max_{x \in S_A(t)} u(x),$$

where $\mathcal{Z}^{ND} \subset \mathcal{Z}$ comprises non-decreasing sequences of sets in $\mathcal{X}$, such that $Z_t \subset Z_{t+1}$ all $t \geq 1$.

Given that final choice of x over y is unrevealing with incomplete search, the ABS characterization relies on an enriched notion of revealed preference. To understand the required enrichment, we consider behavioral patterns that contradict ABS. In doing this, we use the notation $C(A) = B_1; B_2; ...; B_n!$ with $B_i \in \mathcal{X} \cap A$ to indicate that the sets $B_1..B_n$ are chosen sequentially from A, with B_n being the final choice. The following choice process data all contradict ABS.

$$\begin{aligned} C^{\alpha}(\{x, y\}) &= x; y; x! \\ C^{\beta}(\{x, y\}) &= x; \{x, y\}; y! \\ C^{\gamma}(\{x, y\}) &= y; x!;\ C^{\gamma}(\{x, y, z\}) = x; y! \\ C^{\delta}(\{x, y\}) &= y; x!;\ C^{\delta}(\{y, z\}) = z; y!;\ C^{\delta}(\{x, z\}) = x; z! \end{aligned}$$

C^{α} contains a preference reversal: the DM first switches to y from x, suggesting that x is preferred to y. However, the DM then switches back to y, indicating that y is preferred to x. C^{β} involves y first being revealed indifferent to x, as x and y are chosen at the same time. Yet later y is revealed to be strictly preferred to x as x is dropped from the choice set.. In C^{γ} the direction in which preference is revealed as between y and x changes between the two element and three element choice set. C^{δ} involves an indirect cycle, with separate two element sets revealing x as preferred to y, y as preferred to z, and z as preferred to x.

As these examples suggest, the appropriate notion of strict revealed preference in the case of ABS is based on the notion of alternatives being replaced in the choice sequence over time. A DM who switches from choosing y to choosing x at some later time is interpreted by the ABS model as preferring x to y. Similarly, if we ever see x and y being chosen at the same time, it must be that the DM is indifferent between the two alternatives. Hence we capture the revealed preference information implied by the ABS model in the following binary relations.

Definition 3 *Given choice process (X, C), the symmetric binary relation $\sim$ on X is defined by $x \sim y$ if there exists $A \in \mathcal{X}$ such that $\{x, y\} \subset C_A(t)$ some $t \geq 1$. The binary relation $\succ^C$ on X is defined by $x \succ^C y$ if there exists $A \in \mathcal{X}$ and $s, t \geq 1$ such that $y \in C_A(s)$, $x \in C_A(s+t)$ but $y \notin C_A(s+t)$.*

For a choice process to have an ABS representation it is necessary and sufficient for the revealed preference information captured in $\succ^C$ and $\sim$ to be consistent with an underlying utility ordering. The CD characterization of ABS therefore makes use of Lemma 1, a standard result which captures the conditions under which an incomplete binary relation can be thought of as reflecting some underlying complete pre-order. Essentially, we require the revealed preference information to be acyclic.

Lemma 1 *Let P and I be binary relations on a finite set X, with I symmetric, and define PI on X as $P \cup I$. There exists a function $v : X \to \mathbb{R}$ that **respects** P and I:*

$$\begin{aligned} xPy &\implies v(x) > v(y); \\ xIy &\implies v(x) = v(y); \end{aligned}$$

*if and only if P and I satisfy **OWC** (only weak cycles): given $x_1, x_2, x_3, .., x_n \in X$ with $x = x_1 PI x_2 PI x_3 .. PI x_n = x$, there is no k with $x_k P x_{k+1}$.*

Armed with this result, CD establish that the key to existence of an ABS representation is for $\succ^C$ and $\sim$ to satisfy OWC.

Theorem 1 *Choice process (X, C) has an ABS representation iff $\succ^C$ and $\sim$ satisfy OWC.*

This condition is closely related to the standard strong axiom of revealed preference. It is this condition that reduces to the improvement condition that is tested in the experiment described in section 3. The set of equivalent representations of a choice process for which $\succ^C$ and $\sim$ satisfy OWC involve the utility function v respecting $\succ^C$ and $\sim$ on X, and the search correspondence S including at least all objects which have been chosen from all sets A at times $s \leq t$, with permissible additional elements that have utility is strictly below that associated with chosen objects according to v. Hence the more switches there are between objects in the choice process, the more restricted is the set of utility functions that can form part of an ABS representation.

Since the ABS model says nothing about the stopping rule for search, CD augment it with a simple "reservation utility" stopping rule in which search continues until an object is found which has utility above some fixed reservation level, whereupon it immediately ceases. The key to the empirical content of this stopping rule is that one can make inferences as to objects that must have been searched even if they are never chosen. Specifically, in any set in which the final choice has below reservation utility, it must be the case that all objects in the set are searched. Hence final choices may contain revealed preference information. The RBS model embodies the concept of satisficing that Simon [1955] introduce in his pioneering model of bounded rationality, in which he suggested that decision makers do not optimize but rather search until they achieve a "satisfactory" (or reservation) level of utility.

Intuitively, an RBS representation is an ABS representation (u, S) in which a reservation level of utility ρ exists, and in which the above-reservation set $X_u^\rho = \{x \in X | u(x) \geq \rho\}$ plays an important role in the search process. Specifically, search stops if and only if an above-reservation item is discovered. In order to capture this notion formally, CD define $C_A^L = \lim_{t\to\infty} C_A(t)$, as the final choice the DM makes from a set $A \in \mathcal{X}$ as well as limit search sets $S_A^L \equiv \lim_{t\to\infty} S_A(t) \in \mathcal{X}$. Note that, for finite X, the existence of an ABS representation guarantees that such limits are well defined.

Definition 4 *Choice process* (X, C) *has a* ***reservation-based search (RBS)*** *representation* (u, S, ρ) *if* (u, S) *form an ABS representation and* $\rho \in \mathbb{R}$ *is such that, given* $A \in \mathcal{X}$,

R1 *If* $A \cap X_u^\rho = \emptyset$, *then* $S_A^L = A$.

R2 *If* $A \cap X_u^\rho \neq \emptyset$, *then:*

(a) *there exists* $t \geq 1$ *such that* $C_A(t) \cap X_u^\rho \neq \emptyset$;

(b) $C_A(t) \cap X_u^\rho \neq \emptyset \Longrightarrow S_A(t) = S_A(t+s)$ *all* $s \geq 0$.

Condition R1 demands that any set containing no objects above reservation utility is fully searched. Condition R2(a) demands that search must at some point uncover an element of the above-reservation set if present in the feasible set. Condition R2(b) states that search stops as soon as reservation utility is achieved.

As with the ABS model, the key to characterizing the RBS model is to understand the corresponding notion of revealed preference. As RBS is a refinement of ABS, it must be the case that behavior that implies a revealed preference under ABS also does so under RBS. However, the RBS model implies that some revealed preference information may also come from final choice, with sets that contain only below-reservation utility objects being completely searched.

The following cases that satisfy ABS but not RBS illustrate behaviors that must be ruled out:

$$\begin{aligned} C^{\alpha}(\{x,y\}) &= x;y!;\ C^{\alpha}(\{x,z\}) = x!;\ C^{\alpha}(\{y,z\}) = z! \\ C^{\beta}(\{x,y\}) &= x;y!;\ C^{\beta}(\{x,y,z\}) = x! \end{aligned}$$

In the first case, the fact that x was replaced by y in $\{x,y\}$ reveals the latter to be preferred and the former to be below reservation utility. Hence the fact that x was chosen from $\{x,z\}$ reveals z to have been searched and rejected as worse than x, making its choice from $\{y,z\}$ contradictory. In the second, the fact that x is followed by y in the choice process from $\{x,y\}$ reveals y to be preferred to x, and x to have utility below the reservation level (otherwise search must stop as soon as x is found). The limit choice of x from $\{x,y,z\}$ therefore indicates that there must be no objects of above-reservation utility in the set. However, this in turn implies that the set must be fully searched in the limit, which is contradicted by the fact that we know y is preferred to x and yet x is chosen.

In terms of ensuring existence of an RBS representation, the critical question is how to identify all objects that are revealed as having below-reservation levels of utility. As in the above cases, we know that an object must have utility below the reservation level if we see a DM continue to search even after they have found that object. CD call such an object non-terminal. Furthermore, we know that an object must be below reservation utility if, in some choice set, a directly non-terminal element is finally chosen instead of that object. CD define the union of this class of object and the non-terminal objects as indirectly non-terminal.

Definition 5 *Given choice process (X,C) define the non-terminal set $X^N \subset X$ and the indirectly non-terminal set $X^{IN} \subset X$ as follows,*

$$\begin{aligned} X^N &= \{x \in X | \exists A \in \mathcal{X} \text{ s.t. } x \in C_A(t) \text{ and } C_A(t) \neq C_A(t+s) \text{ some } s,t \geq 1\ \}; \\ X^{IN} &= X^N \cup \{x \in X | \exists A \in \mathcal{X},\ y \in X^N \text{ with } x,y \in A \text{ and } y \in C_A^L\}. \end{aligned}$$

Under an RBS representation, final choices in sets with below reservation utility objects contain revealed preference information: when choice is made from two objects $x, y \in X$ either of which is indirectly non-terminal, then we can conclude that the chosen object is preferred. To see this, suppose that y is indirectly non-terminal, hence has below reservation utility. In this case if it is chosen over x it must be that x was searched and rejected. Conversely, suppose that x is chosen over y. In this case either x is above reservation, in which case it is strictly preferred to y, or it is below reservation, in which case we know that the entire set has been searched, again revealing x superior. This motivates the introduction of the binary relation $\succ^L$ on X which gets united with the information from $\succ^C$ to produce the new binary relation $\succ^R$ relevant to the RBS case.

Definition 6 *Given choice process (X, C), the binary relation $\succ^L$ on X is defined by $x \succ^L y$ if $\{x \cup y\} \cap X^{IN} \neq \emptyset$, and there exists $A \in \mathcal{X}$ with $x, y \in A$, $x \in C_A^L$, yet $y \notin C_A^L$. The binary relation $\succ^R$ is defined as $\succ^L \cup \succ^C$.*

The behavioral condition that is equivalent to the RBS model is that the revealed preference information obtained from $\succ^R$ and $\sim$ is consistent with an underlying utility function.

Theorem 2 *Choice process (X, C) has an RBS representation iff $\succ^R$ and $\sim$ satisfy OWC.*

The ABS and RBS models both treat search order as unobservable, and characterize the extent to which it is recoverable from choice process data. This makes it natural to develop stochastic variants, since there is no reason to believe that search from a given set will always take place in the same order. CD therefore generalize the deterministic model to allow for stochasticity. They do this by allowing each choice set to map onto a probability distribution over sequences of chosen objects. The resulting stochastic models turn out to be direct generalizations of their deterministic counterparts. CD show that the stochastic RBS model can capture anomalous choice behavior, such as status quo bias, stochastic choice, and general framing effects.

<1>The Experiment

Having developed a theory of information search that could potentially explain choice "mistakes," our next task was to develop an experimental methodology that would allow us to test these models. These experiments are described in CDM.

The main simplification in the choice process experiment is that CDM make the utility function observable and identical across subjects. To accomplish this, the objects of choice are amounts of money received with certainty. In order to make the choice problem non-trivial, each object is displayed as an arithmetic expression, a sequence of addition and subtraction operations, with the value of the object equal to the value of the sum in dollars. The value of each alternative was drawn from an exponential distribution with $\lambda = 0.25$, truncated at \$35 (a graph of the distribution was shown in the experimental instructions).[1] Once the value of each object was determined, the operations used to construct the object were drawn at random.

Each round began with the topmost option on the screen selected, which had a value of \$0, and so was worse than any other option. To elicit choice process data, subjects were allowed to select any alternative in the choice set at any time, changing their selected alternative whenever they wished. The alternative that the subject currently selected would then be displayed at the top of the screen. A subject who finished in less than 120 seconds could press a submit button, which completed the round as if they had kept the same selection for the remaining time. Typically, a subject took part in a single session consisting of 2 practice rounds and 40 regular rounds, and two recorded choices were actualized for payment, which was added to a \$10 show up fee.

The key to the experimental design is the way in which subjects were incentivized. Rather than simply receiving their final choice, actualized choice was recorded at a random point in time unknown to the experimental subject. Specifically, subjects were instructed that at the end of the round, a random time would be picked from distribution between 1 and 120 seconds according to a truncated beta distribution with parameters $\alpha = 2$ and $\beta = 5$, and the selected alternative at this time would be recorded as the choice for that round.[2]. At any given time, its is therefore optimal for the subject to have selected the alternative that they currently think is the best, as there is a chance that their current selection would be recorded as their choice. We therefore interpret the sequence of selections as choice process data.[3]

[1] For each of the three choice set sizes we generated 12 sets of values, which were used to generate the choice objects at both the low and the high complexity levels.

[2] A graph of this distribution was shown in the experimental instructions. The beta distribution was chosen in order to "front load" the probability of a time being selected in the first minute of the choice round, as most subjects made their choices inside 120 seconds.

[3] In support of this interpretation, many subjects indicated in a follow-up survey that they always selected their most preferred option.

There were six treatments, differing in the complexity of choice object (3 or 7 addition and subtraction operations for each object) and the total number of objects (10, 20 or 40 alternatives) in the choice set. Figure 1 (from CDM) shows a 10 option choice set with objects of complexity 3.

The experimental design creates an environment in which subjects' final choices were suboptimal. Averaging across all treatments, subjects fail to finally choose the best option 44% of the time. Failure rates vary from 11.4% for the size 10, low complexity (3 operations) treatment to 80.9% for size 40, high complexity (7 operations) treatment. These failures of optimality were also significant in terms of dollar amounts, with an average gap of more than $8.00 between the finally chosen and the best option in the largest and most complex choice sets (size 40, complexity 7).

The potential for choice process data to shed light on the above losses derives from the fact that several switches are commonly observed in the pre-decision period. Most individuals do indeed change their selection with consideration time. This is a necessary condition for choice process data to contain more information than standard choice data alone.

<2>Sequential Search

The first question that CDM consider is the extent to which switches in the pre-decision period are from lower to higher value alternatives (this corresponds to "alternative-based" search (ABS) in the general characterization above). Using a standard measure of the failure of consistency with revealed preference (Houtman and Maks [1985]) with measures of statistical power based on the alternative of random selection (as in Bronars [1987]), CDM show that, for the population as a whole, ABS does a good job of describing search behavior. They also identify "ABS types" by comparing each subject's HM Index with the median HM Index of the 1,000 simulations of random data for that subject, which have exactly the same number of observations in each round. have an HM Index lower than the 75th percentile. They focus on the 72 out of 76 subjects with HM indices about the 75th percentile of this distribution.

The prevalence of ABS types suggests that simple search theoretic explanations can help make sense of apparent mistakes. In large choice sets, people still recognize preferred objects and choose them when they come across them. However, their final choices may not be maximal because they do not search through all available alternatives.

<2>Satisficing

CDM use choice process data to shed new light on satisficing behavior. They show that the RBS model describes the experimental data well at both the aggregate and individual level. At the aggregate level, for each treatment there exists possible reservation values such that, on average, subjects continue to search when currently selecting an alternative which is below this reservation level, but stop searching when holding a value above it. This is true even if the data is broken down by total number of searches. This means that a reservation level can be estimated for each treatment (as we describe below). The resulting estimated reservation values also do a good job of describing individual level data: across all treatments subjects behave in line with these reservation levels (i.e. stop searching when holding a value above this level but continue searching when holding a value below it) in approximately 77% of observations.

CDM use standard methods to estimate the reservation utility for each treatment. Specifically all individuals in a given choice environment are assumed to have the same constant reservation value $\overline{v}$ and experience variability ε in this value each time they decide whether or not to continue search. Further, this stochasticity is assumed to enter additively and to be drawn independently and identically from the standard normal distribution. To estimate the reservation level using choice process data, CDM consider each selection made by a subject as a decision node. Search is defined as continuing if a subject switches to another alternative after the current selection. Conversely, search is stopped at a decision node only if the subject made no further selections, pressed the submit button, and the object they had selected was not the highest value object in the choice set. Reservation levels are estimated by maximizing the likelihood of observed decisions.

Not only do the estimated reservation levels do a good job of explaining individual behavior, they also shed light on why the number of mistakes vary from treatment to treatment. CDM find that reservation levels vary systematically with treatment. Reservation levels *decrease* as the objects of choice get more complicated. This explains why mistakes (measured as the gap in value between the chosen option and the best available option) are larger in more complicated choice sets. Reservation levels *increase* as the size of the choice set increases. This increase implies that subjects do better in absolute terms in larger choice sets, but the increase is not sufficient to prevent them from making larger mistakes in bigger choice sets.

While the theoretical interest of the satisficing model is clear, it is perhaps surprising that the experimental results of CDM offer such strong support to this stark model. A partial explanation may lie in the connection between the experimentally identified reservation stopping rules and optimal stopping rules in a model with a fixed psychic cost of search and independently drawn object valuations. CDM show that a fixed reservation strategy is optimal in this model. Yet there are some conflicts between this model and the experimental findings. Specifically, optimal reservation levels are independent of the size of the choice set in the optimizing model, yet increasing in the experiment. Understanding this finding is a priority in ongoing research.

<2>Search Order

Choice process data provide insight into the order in which people search through available objects, and this information can help predict when subjects will do badly in particular choice sets. CDM analyzed two factors that can determine search order: screen position and object complexity. In order to explore both factors, they ran an additional experimental treatment which contained objects of varying complexity. This treatment contained choice sets of size 20, and the objects in each set varied in complexity from between one and nine operations. They ran the new treatment on 21 subjects for a total of 206 observed choice sets.

In the context of these experiments, CDM show that average search behavior has systematic patterns. On average, subjects search the screen from top to bottom: screen position is higher for later searched objects. They show also that subjects tend to search from simple to complex objects. Perhaps more surprising is evidence of individual differences in the search patterns of individual subjects. Some subjects behave in a manner consistent with “Top-Bottom” (TB) search, while others are consistent with “Simple-Complex” (SC) search. The former are subjects whose search order takes them from the top to the bottom of the screen, while the latter are subjects whose search takes them from simple to complex objects.

The experiment reveals that the differences in search order impact final choices. In a round in which the highest valued item is very short and occurs at the end of the list, TB searchers find it less often than do SC searchers. Conversely when the highest valued item is very long and occurs very early in the list, TB searchers find it more often than do SC searchers.

<1>Choice Alone

Our central claim in this chapter is that our enhanced choice experiment helps us to understand choice behavior in a way that would not be possible using choice alone. In order to support this claim, we need to show two things. First, that our method for eliciting the enhanced choice data does not distort the behavior of our subjects to such an extent that we learn very little about standard choice environments. Second, that the additional data that we collected does in fact add to our understanding of choice

To investigate these two points, CDM ran a "pure choice" version of the experimental design removing the incentives relating to the pre-decision period. The standard choice experiment made use of exactly the same treatments as the choice process experiments: choice sets contained 10, 20 or 40 alternatives, with the complexity of each alternative being either 3 or 7 operations. Moreover, exactly the same choice sets were used in the choice process and standard choice experiments. The subjects in the pure choice experiment took part in a single experimental session consisting of 2 practice rounds and between 27 and 36 regular rounds, drawn from all 6 treatments. At the end of the session, two regular rounds were drawn at random, and the subject received the value of the selected object in each round, in addition to a $10 show up fee. Each session took about an hour, for which subjects earned an average $32. In total we observed 22 subjects making 657 choices.[4]

We find similar patterns of final choices in the pure choice and choice process environments. There are somewhat fewer mistakes in the pure choice experiment: averaging across all treatments, subjects fail to select the best option 38% of the time, compared to 44% of the time in the choice process experiment. However, the comparative statics are similar in the two cases: Mistakes increase both with the size of the choice set and the complexity of alternatives, with failure rates varying from 7% for the size 10, low complexity (3 operations) treatment to 65% for size 40, high complexity (7 operations) treatment. These failures of rationality remain significant in terms of dollar amounts, with average loss of $7.12 in the size 40, high complexity treatment. The pattern of mistakes was also similar between the pure choice and choice process settings: when CDM compare the distribution of final choices using Fisher's exact test, only 12 of the 60 choice sets have distributions that are significantly different at the 5% level.

To the extent that there is a difference in the quality of final choices between the choice process

[4] One difference was that the pure choice experiments were run without time limits. When comparing with the choice process outcomes, CDM focus only on rounds from the choice process experiment in which the subject pressed the submit button before the allotted 120 seconds, and so did not hit the binding time constraint.

and pure choice treatments, it goes in the expected direction. The incentive to continue searching is higher in the standard choice experiment, since it is certain that any identified improvements will be implemented. The corresponding probability is less than one in the choice process experiment, and falls toward zero as the 2 minutes come to an end. In this light, it is noteworthy how limited was the impact of the incentive changes induced by the choice process interface.

There is one other source of evidence on the similarity in decision making with and without the enhanced incentives in the choice process experiment. The experimental design allowed subjects in the pure choice experiment to select options prior to their final choice just as they could in the choice process experiment. The only difference was that in the standard choice experiment, there was no incentive for them to do so. CDM found that subjects still did record switches of their own volition even without incentives, that the resulting selections broadly satisfied ABS and RBS, and that reservation utilities exhibited the same qualitative patterns as in the incentivized experiment. Essentially all of the results above concerning the nature of the search and decision process from the choice process experiments are closely mirrored using data from the pre-decision period in the pure choice experiment despite the absence of incentives.

How much could we have learned about information search and choice had we observed only pure choice, and ignored the pre-decision period? The answer is very little, and much of it wrong. On the positive side, one would learn that choices are made more poorly in the larger and more complex decision sets. On the negative side, one would nave no way of testing various explanations for what is behind these poor decisions. With choice data alone, one could not test the ABS or RBS model, or make reliable inferences about reservation utility levels. If all one observed were final choices then any data set can be explained perfectly by a model in which the reservation level is zero, and whatever is chosen is the first object searched. Thus it is infeasible to estimate reservation levels, and compare how they change with the environment. Thus, the extra information in choice process allows us to understand what it is that drives suboptimal choice and estimate otherwise hidden reservation parameters

A second advantage of choice process data is that it allows us to recover revealed preference information in the case of incomplete search. In environments such as these, where all alternatives are not evaluated, the eventual choice of one object over another does not necessarily convey preference, as the decision maker may be unaware of the unchosen alternative. Standard choice data does not therefore reveal any preference. In contrast when one has access to choice process data, the switch from one alternative to another *does* convey revealed preference information under the assumption of the ABS model, as the fact that the former alternative was chosen at one time indicates that the decision maker was aware of its existence.

<1>Methodology

The research outlined above is part of a methodologically-oriented agenda in the area of "neuroeconomics." This field has recently been the subject of much controversy concerning its definition and its substance. An initial salvo was fired by Camerer, Loewenstein, and Prelec [2005] who argued that neurological data would revolutionize our understanding of choice. Gul and Pesendorfer [2008] fired back hard with the claim that non-standard data is essentially irrelevant to economics, which is interested only in the act of choice.

Following this harsh exchange, the center of the active debate on neuroeconomics concerns what are appropriate forms of non-standard data to explore to better understand choice, and the extent to which these data need themselves to be modeled. Here there are many flowers that continue to bloom. Camerer [2008] outlines a very wide array of non-standard data that are potentially interesting to those seeking to understand choice. Search in particular has been a major spur to the development of psychological data. Herbert Simon developed "protocol analysis" to augment choice data with highly structured vocalized descriptions of the decision making process (Ericsson and Simon [1984]); time to decide has been the focus of much research (e.g. Armel, Beaumol, and Rangel [2006] and Wilcox [1993]), as have the order of information search as revealed by Mouselab (e.g. Payne, Bettman and Johnson [1993], Ho, Camerer, and Weigelt [1998], and Gabaix et al. [2006]); eye movements (e.g. Wang, Spezio and Camerer [2006] and Reutskaja et al. [2008]); and neuroscientific observations.

The program of neuroeconomic research in which we are engaged, and to which the work outlined herein contributes, involves a particularly tight relationship between non-standard data and economic theory. We see the tension between tightly constrained decision theory and massive volumes of new psychological data as potentially damaging to the social nature of the research enterprise (see Caplin [2008] for an in depth exposition). The concern is that such open-ended constructs as decision making frames, mental accounts, and rules of thumb are flexible enough to account for any pattern of observations, and subjective enough to defy common definition.

We believe that the key to avoiding this potential communication breakdown is to internalize the profound strength of the data theoretic ("axiomatic") approach introduced into economics by Samuelson [1938].

It is ironic that the axiomatic approach is traditionally seen as connected to a standard concept of choice among available alternatives. There is no necessary connection of this nature. Indeed it is our view that axiomatic methods are made ever more essential by data proliferation. Application of the axiomatic method ensures that new data earn their keep by opening up new observable phenomenon. In principle, axiomatic methods represent an ideal method for unifying psychologically sophisticated decision theory with experimental economics. It is also methodologically incoherent to argue that axiomatic methods apply best to a particular designated data set, comprising "standard" choices. We see no valid distinction between choice and non-choice data. To take an extreme case, the pulse can be modeled as chosen just as much as can the standard choice of apples over oranges. While it may be that the former is more tightly constrained by physical laws, even this is debatable. After all, the goal of choice theory is to treat choice itself as mechanically as possible.

The first work in which we jointly characterize properties of standard choice data and non-standard data relates to the neurotransmitter dopamine. In that context, Caplin and Dean [2009b] identified the precise characteristics of the standard theory in which dopamine provides a reward prediction error signal, while Caplin, Dean, Glimcher, and Rutledge [2010] provided the corresponding experimental tests, which were broadly positive. The current work is the second example, but is in many ways more fundamental to the methodology. It takes full advantage of the researcher's freedom to specify non-standard data that is experimentally observable, and for which a ready made theory exists that is very close to standard choice theory. An extremely well developed theory suggests that search is sequential and investigates optimal search, which is often of the reservation variety. Moreover, the very first breakdown of revealed preference relates to incomplete search, a point that was noted early on by Block and Marshak [1960] in their pioneering model of stochastic choice.

Our investigation of choice process data reflects the joining of natural streams: study of non-standard data and axiomatic methods of choice theory. Interestingly, Campbell [1978] had previously developed a theory of this data tape with respect to an early model of the decision making procedure. In fact it is in many respects a natural data tape for a theorist, and ABS and RBS are natural first formulations of boundedly rational decision models.

<1>Concluding Remarks

There are several obvious next steps in the research agenda related to the choice process. One such step is to join choice process data with additional observations on the search process, including mouse movements, time between switches, eye movements, and neurological measurements. We expect eye movements to be of particular value in helping us understand the nature of search. While less well studied than standard choice behavior, opening up to these enriched observations may be very important in analyzing possible alternative modes of search, such as "characteristic based" procedures in which objects are compared on a facet-by-facet basis.

With regard to applications, we are particularly interested in variants of the choice process model and experiment that give insight into financial decision making over the Internet. It is intuitively clear that most of us are incapable of making fully informed financial decisions, and that the mode of presentation can substantively impact both what we understand and what we choose. The choice process interface represents only a starting point in terms of the observational enrichments required to further our understanding of these effects.

It is in some ways surprising that economists have focused so little prior attention on how well understood are the various options in any given decision making context. While research has now begun on the many settings in which subjective "consideration sets" may be strictly smaller than the objectively available set of choices, nothing of equal power has replaced the principle of revealed preference.[5] It is the organizing power that this principle introduces that led to our experimental investigation of artificially enhanced choice data.

We see our agenda as illustrating one of the advantages of economic experiments over field experiments. Our experiments really require a controlled environment in which the process of choice is subject to "un-natural" manipulation and to observation. It would be hard if not impossible either to manipulate or to adequately observe the act of choice in a field experiment designed to be naturalistic.

<1>Bibliography

[5] Rubinstein and Salant [2006] study choices made from sets presented in "list" order, effectively making the order of search observable. Masatlioglu and Nakajima [2009] characterize choices that result from iterative search of "consideration sets" related to each alternative. They focus on how final choice is related to an initial (externally observable) reference point.

Armel, K. Carrie, Aurelie Beaumol, and Antonio Rangel. 2007. The Computation of Decision Values in Simple Economic Choice. *Working Paper*, Caltech.

Block, H. D., and J. Marschak. 1960. Random Orderings and Stochastic Theories of Response. *Contributions to Probability and Statistics.* Essays in honor of Harold Hotelling. Ed. I. Olkin Stanford University Press, Stanford, CA.

Bronars, Stephen. 1987. The Power of Nonparametric Tests of Preference Maximization. *Econometrica*, 55(3): 693-698.

Camerer, Colin, George Loewenstein, and Drazen Prelec. 2005. Neuroeconomics: How Neuroscience Can Inform Economics. *Journal of Economic Literature*, Vol. 43, 9–64.

Campbell, Donald. 1978. Realization of Choice Functions." *Econometrica* 46: 171-180.

Caplin, Andrew. 2008. Economic Theory and Psychological Data: Bridging the Divide. In *The Foundations of Positive and Normative Economics: A Handbook*, eds. A. Caplin and A. Schotter. Oxford University Press.

Caplin, Andrew, and Mark Dean. 2008. Dopamine, Reward Prediction Error, and Economics." *Quarterly Journal of Economics.* 123(2): 663–701

Caplin, Andrew, and Mark Dean. 2009. Search, Choice and Revealed Preference." New York University, *mimeo.*

Caplin, Andrew, Mark Dean, Paul Glimcher, and Rob Rutledge. 2009. Choice Anomalies, Search, and Revealed Preference. *Quarterly Journal of Economics*, forthcoming.

Caplin, Andrew, Mark Dean, and Daniel Martin. 2009. "Search and Satisificing." New York University, *mimeo.*

Ericsson, K. & H. Simon. 1984. *Protocol Analysis.* Cambridge, MA, MIT Press.

Gabaix, Xavier, David Laibson, Guillermo Moloche, and Stephen Weinberg. 2006. Costly Information Acquisition: Experimental Analysis of a Boundedly Rational Model. *American Economic Review*, 96(4): 1043-1068.

Gul, Faruk, and Wolfgang Pesendorfer. 2008. The Case for Mindless Economics. In The Foundations of Positive and Normative Economics, ed. Andrew Schotter and Andrew Caplin.

Ho, Teck Hua, Colin Camerer, and Keith Weigelt. 1998. Iterated Dominance and Iterated Best Response in Experimental p-Beauty Contests. *American Economic Review*, 88, 947-969.

Houtman, Martijn, and J. A. H. Maks. 1985. Determining all Maximal Data Subsets Consistent with Revealed Preference. *Kwantitatieve Methoden*, 19: 89-104.

Masatlioglu, Yusufcan, and Daisuke Nakajima. 2008. Choice by Iterative Search. Unpublished.

Payne, J. W. , J. R. Bettman, and E. J. Johnson. 1993. *The Adaptative Decision Maker*. Cambridge, MA: Cambridge University Press.

Reutskaja, E., J. Pulst-Korenberg, R. Nagel, C. Camerer, and A. Rangel. 2008. Economic Decision-Making under Conditions of Extreme Time Pressure and Option Overload: An Eyetracking Study. Unpublished.

Rubinstein, Ariel, and Yuval Salant. 2006. A Model of Choice from Lists. *Theoretical Economics*, 1(1): 3-17.

Samuelson, Paul. 1938. A Note on the Pure Theory of Consumer's Behavior." *Economica*, 5, 61 -71.

Simon, Herbert. 1955. A Behavioral Model of Rational Choice. *Quarterly Journal of Economics*, 69 (1), pp 99-118.

Wang, Joseph, Michael Spezio, and Colin Camerer. 2006. Pinocchio's Pupil: Using Eyetracking and Pupil Dilation To Understand Truth-telling and Deception in Games. *mimeo*, Caltech.

Wilcox, Nathaniel T. 1993. Lottery Choice: Incentives, Complexity and Decision Time. *The Economic Journal*, Vol. 103, No. 421 , pp. 1397-1417.