

# Neuroeconomic Foundations of Economic Choice—Recent Advances<sup>†</sup>

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**T**he brain controls human behavior. Economic choice is no exception. Recent studies have shown that experimentally induced variation in neural activity in specific regions of the brain changes people's willingness to pay for goods, renders them more impatient, more selfish, and more willing to violate social norms and cheat their trading partner (Camus et al., 2009; Figner et al., 2010; Knoch, Pascual-Leone, Meyer, Treyer, and Fehr, 2006; Baumgartner, Knoch, Hotz, Eisenegger, and Fehr, 2011; Ruff, Ugazio, and Fehr, 2011; Knoch, Schneider, Schunk, Hohmann, and Fehr, 2009). These studies use noninvasive brain stimulation techniques such as transcranial magnetic stimulation (TMS) and transcranial direct current stimulation (tDCS), which enable the researcher to exogenously increase or decrease neural activity in specific regions of the cortex before subjects make decisions in experimental tasks that elicit their preferences. Such findings demonstrate that neural activity *causally* determines economic choices, and they provide motivation for studying the neurobiological and computational mechanisms at work in economic behavior.

Neuroeconomics combines methods and theories from neuroscience, psychology, economics, and computer science to investigate three basic questions: 1) What are the variables computed by the brain to make different types of decisions, and how do they relate to behavioral outcomes? 2) How does the underlying

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neurobiology implement and constrain these computations? 3) What are the implications of this knowledge for understanding behavior and well-being in various contexts: economic, policy, clinical, legal, business, and others? The ultimate goal is to produce detailed computational and neurobiological accounts of the decision-making process that can serve as a common foundation for understanding human behavior across the natural and social sciences (Wilson, 1999).

Traditionally, economists have not been interested in the neural processes underlying human choice. This lack of interest is driven by the theory of revealed preference, which is one of the triumphs of twentieth century economics. Most economic models assume that individuals make choices as if maximizing a prespecified utility function, subject to feasibility and informational constraints. The revealed preference view is based on a well-known result: as long as observed choices satisfy some basic consistency axioms, such as the Weak Axiom of Revealed Preference, they are consistent with the maximization of some latent utility function (Houthakker, 1950; Samuelson, 1938). As a result, traditional economic models are “as if,” as opposed to “as is,” descriptions of decision making.

In contrast, neuroeconomists are interested in the actual computational and neurobiological processes behind human behavior. The neuroeconomic approach aims for “structural” or “as is” models of decision making. Because neuroeconomics is a very young discipline, a sufficiently sound structural model of how the brain makes choices is not yet available. However, the contours of such a computational model have begun to arise. Furthermore, given the rapid progress that has already been made, there is reason to be hopeful that the field will eventually put together a satisfactory structural model.

This article has two main goals. First, we provide an overview of what has been learned about how the brain makes choices in two types of situations: simple choices among small numbers of familiar stimuli (like choosing between an apple or an orange), and more complex choices involving tradeoffs between immediate and future consequences (like eating a healthy apple or a less-healthy chocolate cake). In each case, we describe the emergent computational model of the underlying choice process as well as the neuroeconomic experiments that test the different components of the model.<sup>1</sup> Second, we show that even at this early stage in the field, insights with important implications for economics have already been gained.

We will show below, for example, that one important implication is the prevalence of systematic mistakes in economic choices. Neural activity is stochastic by its very nature and thus the neural computations necessary for making choices

<sup>1</sup> Given the scope of this essay, we do not discuss many important areas of neuroeconomics research that should be of interest to economists, including how the brain learns to assign values, the neurobiology of social preferences, the neurobiology of strategic choice, the neurobiology of financial decision making, and neural mechanism design. A list of citations for these topics is available in online Appendix A, available with this paper at (<http://e-jep.org>).

are stochastic. For this reason, neuroeconomics can provide a neural foundation for random utility models. However, while random utility models assume that preferences are stochastic and that choices always reflect underlying preferences, neuroeconomic research suggests that the choice process can be systematically biased and suboptimal. For example, the computation and the comparison of decision values underlying goal-directed behavior may be biased because decision-makers may fail to take into account the relevant attributes of experienced utility. In fact, as we will show below, neuroeconomic research indicates that consumption choices can be biased by simple manipulations of subjects' visual attention and the opportunity costs of time, thus providing insights into how marketing actions can affect the probability of mistakes. The observed pattern of the neuronal encoding of decision values also implies that choices will fail to satisfy the independence of irrelevant alternatives, which is at odds with the axioms of many (random) utility models. In addition, the pattern of the neuronal encoding of decision values implies that mistakes are more likely to occur if the range of values that subjects need to consider is bigger. One consequence of this line of research is that one cannot simply use revealed preferences to measure welfare but that more elaborate procedures are required. Taken together, these findings and implications suggest that neuroeconomics contributes to a positive theory of the mistakes that people make in their choices, with potentially important consequences for positive and normative economics.

### **Simple Choices: Computational Model and Neuroeconomic Evidence**

Simple choices are the simplest instance of economic decision making that can be studied using the neuroeconomics approach. They involve choices between a small number of familiar goods, with no informational asymmetries, strategic considerations, or self-control problems. A typical example is whether to choose an apple or an orange for dessert.

At first sight, these choices are not terribly interesting for an economist. However, they are invaluable for neuroeconomics because they allow us to study the computational and neurobiological basis of decision making in the absence of complicating factors. The hope is that the principles and insights learnt in the simple case will also be at work in more complicated and interesting problems. Indeed, even at our current limited level of understanding, the insights that have already been obtained about simple choice have useful implications for economics.

We begin the discussion by describing the five key components of the computational model of simple choice that is arising from the neuroeconomics literature. Closely related versions of the model have been proposed by Glimcher (2010), Kable and Glimcher (2009), Padoa-Schioppa (2011), and Rangel and Hare (2010).

### 1. The brain computes a decision value signal for each option at the time of choice.

In this model, economic choice is driven by the computation and comparison of “decision value” signals. In particular, the model assumes that the decision values are computed from the instant the decision process starts (for example, when a choice pair is displayed to a subject on a computer screen) to the moment the choice is made (for example, when the subject indicates a choice by, say, pressing a button). Decision values should be thought of as signals computed at the time of choice that forecast the eventual hedonic impact of taking the different options. Because choices are made by computing and comparing decision values, these signals causally drive the choices that are made: options that are assigned a higher decision value will be more likely to be chosen.<sup>2</sup>

The existence of decision value signals at the time of choice might be the single most frequently tested hypothesis in neuroeconomics, as well as the most systematically replicated finding thus far.<sup>3</sup> Multiple human studies using functional magnetic resonance imaging (fMRI) and electro-encephalography (EEG), as well as single neuron recordings in nonhuman primates, have shown that neural activity in an area of the ventromedial prefrontal cortex increases with behavioral measures of the decision values assigned to options at the time of choice.

Since these types of studies are unfamiliar to economists, it is useful to begin by explaining their basic logic. How does one test that the brain encodes a certain variable—say, decision values—at a particular time in the choice process? The typical experiment has three main components. First, some form of behavioral data is used to estimate the value that the brain assigned to the signal of interest. These behavioral data are sometimes obtained in a separate task: for example, in the case of decision values, by asking subjects to provide incentive-compatible bids for each option used in an experiment, or to provide “liking” ratings. In other experimental designs, the values can be inferred directly from the pattern of choices (for example, Chib, Rangel, Shimojo, and O’Doherty, 2009; Padoa-Schioppa and Assad, 2006). Second, a measurement of neural activity is taken during the choice process in particular brain areas. The three most popular techniques used in neuroeconomic studies include fMRI, EEG, and (in animal studies) single neuron *in vivo* recordings.<sup>4</sup> Third, statistical methods are used to test if neural activity during the

<sup>2</sup> It is important to emphasize that this component of the model is not empty or tautological, since there is no *a priori* reason why the brain must make choices by computing and comparing decision values. For example, choices could be made using learnt stimulus-response associations (for example, when a red light is present, press the left lever) or based on the perceptual properties of the options (for example, choose the item with the highest visual contrast). In fact, behavior may be largely driven by these alternative types of processes in sufficiently simple organisms such as nematodes.

<sup>3</sup> For a detailed list of references to the literature showing where and when decision values are computed, see online Appendix B, available with this paper at (<http://e-jep.org>).

<sup>4</sup> The methods have relative advantages and disadvantages. fMRI is noninvasive, provides measures of aggregate neural activity in relatively anatomically specific regions (in the order of 0.5–3.0 mm<sup>3</sup>), but it has poor temporal resolution (typically about 0.5 Hz). EEG is also noninvasive, and it provides extremely fine temporal resolution, but it has much poorer anatomical or spatial resolution than fMRI. Single unit

period of interest is modulated by the signal (or signals) of interest. If the neural activity is statistically significantly related to the signal of interest, then this is taken to be evidence consistent with the hypothesis that activity in that neural substrate encodes the signal.

An example of a paper providing evidence for the existence of decision values is Plassmann, O’Doherty, and Rangel (2007). Hungry subjects were shown a picture of a familiar food snack in every trial and had to decide how much to bid for the right to eat it at the end of the experiment, while neural activity was measured with fMRI. The bids provide a behavioral measure of the decision values computed in every trial. The study found that activity in the area of the brain under study during the choice period correlated with the bids, which provides evidence for the hypothesis that the brain computes decision values at the time of choice. This finding has been replicated in multiple studies using distinct choice objects (lotteries, foods, donations to charity, trinkets), distinct valuation paradigms (price purchase decisions, auction formats, binary choices, liking ratings), and distinct choice speeds (from one to several seconds). Follow-up studies have shown that decision values are encoded in the same area of the ventromedial prefrontal cortex in more complex choice settings: choices among gambles (Levy, Snell, Nelson, Rustichini, and Glimcher, 2010; Tom, Fox, Trepel, and Poldrack, 2007); delayed monetary payments (Kable and Glimcher, 2007); and charitable donations (Hare, Camerer, Knoepfle, and Rangel, 2010).

A related class of studies has asked if the same area of the ventromedial prefrontal cortex encodes the decision values for choices among both appetitive and aversive items (Litt, Plassmann, Shiv, and Rangel, 2010; Plassmann, O’Doherty, and Rangel, 2010; Tom, Fox, Trepel, and Poldrack, 2007). The distinction between appetitive and aversive items is unfamiliar to economists, but is important in psychology and neuroscience. An item is called “appetitive” if an animal would work to consume it (for example, sugar when hungry) and “aversive” if an animal would work to avoid it (for example, an electric shock). A common hypothesis in psychology is that choices among appetitive items, sometimes called approach choice, and choices among aversive items, sometimes called avoidance choice, involve separate systems (Larsen, McGraw, Mellers, and Cacioppo, 2004). These studies are important because they show that, at least in the case of simple choice, the same area of the brain seems to encode the decision value for both types of choices, thus providing evidence against the multiple system hypothesis.<sup>5</sup>

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recordings allow the measurement of activity in single neurons with very high temporal resolution, but this method is extremely invasive. Thus, although the method is pervasive in animal studies, it is rare in humans. An additional advantage of fMRI and EEG over single unit recordings is that they allow the simultaneous measurement of activity in the entire brain, which is critical for studying how the computations carried out in different brain regions affect each other.

<sup>5</sup> This finding is also important because it rules out the possibility that the activity in areas of the brain thought to encode decision values can be attributed to attention or saliency responses, which are alternate signals that increase with the absolute value of the items and that have been found in other cortical areas (Litt, Plassmann, Shiv, and Rangel, 2010; Roesch and Olson, 2004).

Clearly, these findings constitute only preliminary evidence, and further tests must be carried out. Of particular interest is establishing that the decision value signals causally affect choices. The existing evidence suggests that the decision value signals are precursors, and not consequences, of the choice process. The ventromedial prefrontal cortex seems to encode decision values for all options being considered before the choice is made, and the signals do not depend on which option is chosen (Hare, Schultz, Camerer, O'Doherty, and Rangel, forthcoming; Padoa-Schioppa and Assad, 2006; Wunderlich, Rangel, and O'Doherty, 2010). Also, individuals with damage in the relevant areas of the ventromedial prefrontal cortex are unable to make consistent choices, which suggests that this part of the brain plays a necessary role in computing reliable decision value signals (Fellows and Farah, 2007). In addition, although difficult, it is possible to investigate the causality of these signals by experimentally manipulating the value signal in the ventromedial prefrontal cortex and examining the resulting behavioral changes. In a recent study, for example, Baumgartner, Knoch, Hotz, Eisenegger, and Fehr (forthcoming) down-regulate the value signal in the ventromedial prefrontal cortex using transcranial magnetic stimulation in the dorsolateral prefrontal cortex. This down-regulation makes the activity of the ventromedial prefrontal cortex less sensitive to inputs, which renders the value signals encoded here weaker and produces sizable changes in behavior.<sup>6</sup>

## **2. The brain computes an experienced utility signal at the time of consumption.**

The brain needs to keep track of the consequences of its decisions to learn how to make choices in the future. A key component of such learning is the computation of an experienced utility signal at the time of consumption that reflects the actual consequences for the organism of consuming the chosen option.<sup>7</sup>

We emphasize that decision values are distinct from the experienced utility signal: decision values are forecasts about the experienced utility signal that will be computed at the time of consumption.<sup>8</sup> Indeed, decision values and experienced utility need not agree with each other. It is a priori possible that a person might

<sup>6</sup> Pharmacological manipulations also affect brain circuitry and can thus have important causal effects: The neuropeptide oxytocin has been shown to increase trusting behavior (Kosfeld, Heinrichs, Zak, Fischbacher, and Fehr, 2005). The sex hormone testosterone increases bargaining offers in the ultimatum game (Eisenegger, Snodgrass, Heinrichs, and Fehr, 2010) and honesty in an honesty game (Wibral, Dohmen, Kingmüller, Weber, and Falk, 2011). The depletion of the neurotransmitter serotonin increases the rejection rate of responders in the ultimatum game (Crockett, Clark, Tabibnia, Lieberman, and Robbins, 2008) while the administration of benzodiazepines reduces the rejection rate (Gospic et al., 2001).

<sup>7</sup> The study of how experienced utility signals are used by the brain to update future decision values is an active and very important area of research in neuroeconomics, but we do not discuss it here. See Niv and Montague (2008) for an excellent review.

<sup>8</sup> The neuroeconomic distinction between decision value and experienced utility signals parallels the distinction between decision utility and experienced utility that is often made by behavioral economists (Kahneman, Wakker, and Sarin, 1997).

have a higher decision value for apples than for oranges, but that experienced utility might be the opposite. This should not happen often in a well-performing organism, but it cannot be ruled out in all cases by assumption. Understanding the circumstances under which the two signals are in agreement or disagreement is a critical question in neuroeconomics.

Where in the brain are the experienced utility signals computed, and what are the differences between the processes involved in computing decision values and those involved in computing experienced utilities? The body of evidence here is more preliminary than for the case of the decision values. This is partly driven by a technical difficulty: it is quite difficult to induce controlled consumption experiences in humans while they are lying inside an fMRI scanner, and it is difficult to measure experienced utility reliably in animals.

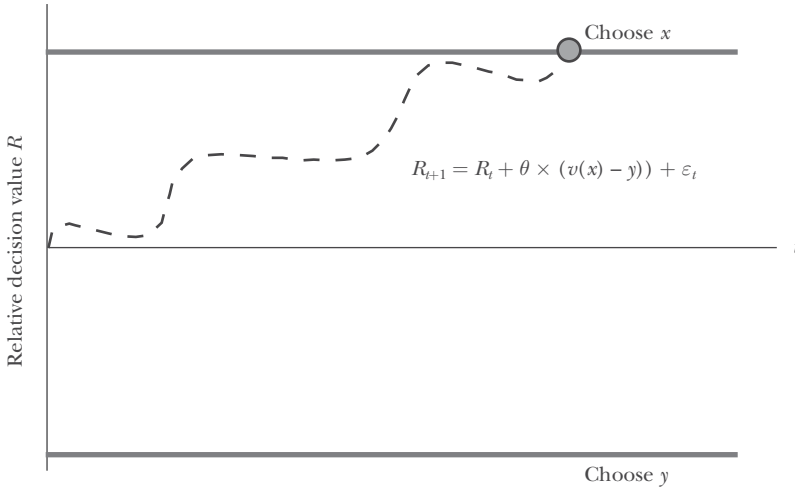
Nonetheless, several studies have found that such signals are present in various parts of the orbitofrontal cortex and the nucleus accumbens at the time of consuming a variety of goods including music, liquids, foods, and art (Blood and Zatorre, 2001; de Araujo, Rolls, Kringelbach, McClone, and Phillips, 2003; Kringelbach, O'Doherty, Rolls, and Andrews, 2003; McClure, Li, Tomlin, Cypert, Montague, and Montague, 2004; Rolls, Kringelbach, and Araujo, 2003; Small, Gregory, Mak, Gitelman, Mesulam, and Parrish, 2003).

Neuroeconomic studies have also begun to characterize some novel properties of the experienced utility signals. Koszegi and Rabin (2006, 2009, 2007) have proposed that experienced utility depends not only on what is consumed, but also on the extent to which that consumption was expected. In particular, they propose that positive surprises increase experienced utility, and that negative surprises decrease it. Bushong, Rabin, Camerer, and Rangel (2011) used fMRI to test this hypothesis and found that activity in the same areas of orbitofrontal cortex previously associated with experienced utility computations exhibit the predicted surprise effects. Plassmann, O'Doherty, Shiv, and Rangel (2008) used a related approach to investigate the extent to which the pleasure derived from drinking a wine depends only on its physiological properties, or whether this pleasure is also modulated by beliefs about the price of the wine. Subjects were asked to drink wines while in the scanner and told the price of each one. Unbeknown to the subjects, the same wine was described at two different prices in different trials: the real retail price and a fictitious one. They found that activity in the areas of orbitofrontal cortex associated with the computation of experienced utilities also increased with the stated wine prices.

### **3. Choices are made by comparing decision values using a “drift-diffusion model.”**

The drift-diffusion model was developed by psychologist Roger Ratcliff to explain the accuracy and response times in any task involving binary responses that can be elicited in a handful of seconds (Ratcliff, 1978; Ratcliff and McKoon, 2008). Examples of such tasks include identifying which of two visual stimuli is larger or brighter, or which of two numbers is larger. The drift-diffusion model can also be

Figure 1

**Graphical Description of the Drift-Diffusion Model**

Source: Authors.

applied to the comparison of decision values. For simplicity, consider the case of a binary choice involving two options,  $x$  and  $y$ . Krajbich and Rangel (2011) present a generalization to multi-item choice. As Figure 1 illustrates, a binary choice is made by dynamically computing a relative decision value signal, denoted by  $R$ , that measures the value difference of  $x$  versus  $y$ . The signal starts at zero and at every instant  $t$  evolves according to the formula

$$R_{t+1} = R_t + \theta \times (v(x) - v(y)) + \varepsilon_t,$$

where  $R_t$  denotes the level of the signal at instant  $t$  (measured from the start of the choice process),  $v(x)$  and  $v(y)$  denote the decision value that is assigned to the two options,  $\theta$  is a constant that affects the speed of the process, and  $\varepsilon_t$  denotes an independent and identically distributed error term with variance  $s^2$ . The process continues until a prespecified barrier is crossed:  $x$  is chosen if the upper barrier at  $B$  is crossed first, and  $y$  is chosen if the lower barrier at  $B$  is crossed first.

The drift-diffusion model has several important features. First, since the relative decision value signal evolves stochastically, choices are inherently noisy, and the amount of noise is proportional to the parameter  $s^2$ . The stochasticity of the relative decision value is a consequence of the inherent stochasticity of neuronal activity. Second, the model predicts that the probability of choosing  $x$  is a logistic function of the difference in the decision value signals  $[v(x) - v(y)]$  (Krajbich, Armel, and Rangel, 2010; Milosavljevic, Malmaud, Huth, Koch, and Rangel, 2010; Ratcliff and McKoon, 2008). Third, given the stochasticity of choice, there is always



a positive probability that individuals will choose the option with the lowest decision value. This probability increases with the difficulty of the choice (as measured by how small is the value  $|v(x) - v(y)|$ , and decreases with the parameter  $\theta$  and with the height of the barriers. Indeed, the model makes specific predictions about how the shape of the reaction time distribution varies with the difficulty of the choice and with the parameters of the model.

The algorithm implemented by the drift-diffusion model might seem like an unnecessarily cumbersome solution to a straightforward maximization problem, but there is a beautiful and deep reason why it has evolved. From the brain's point of view, decision values are estimated with noise at any instant. If the instantaneous decision value signals are computed with identical and independently distributed Gaussian noise, then the drift-diffusion model implements the optimal statistical solution to the problem, which entails a sequential likelihood ratio test (Bogacz, Brown, Moehlis, Holmes, and Cohen, 2006; Gold and Shadlen, 2002, 2007). The intuition for why this is the case is straightforward. The relative decision value  $R_t$  can be thought of as the accumulated evidence in favor of the hypothesis that the alternative  $x$  is better (when  $R_t > 0$ ), or the accumulated evidence in favor of the alternative hypothesis (when  $R_t < 0$ ). The more extreme these values become, the less likely it is that the evidence is incorrect. The probability of a mistake can be controlled by changing the size of the barriers that have to be crossed before a choice is made. As a result, the drift-diffusion model implements an optimal statistical solution to the information problem faced by the brain.

The components of the drift-diffusion model have empirically been tested using both behavioral and neural data. Behaviorally, Milosavljevic, Malmaud, Huth, Koch, and Rangel (2010) showed pictures of familiar food items to subjects, one at a time, and asked them to decide whether they wanted to eat them at the end of the experiment. Before the choice task, they obtained independent measures of the decision values by asking subjects to rate how much they would like to eat them at the end of the experiment. They found that it was possible to find parameters of the basic drift-diffusion model that generated a remarkable quantitative match between the predicted and observed distribution of choices and reaction times. This match provides strong behavioral evidence in favor of this component of the model because the drift-diffusion model makes very strong quantitative predictions about the shape of the choice and response time curves, and how they relate to each other.

Two recent studies have used fMRI to identify areas involved in comparing decision values (Basten, Biele, Heekeren, and Fiebach, 2010; Hare, Schultz, Camerer, O'Doherty, and Rangel, forthcoming). Hare, Schultz, Camerer, O'Doherty, and Rangel (forthcoming) argue that a brain area involved in implementing the drift-diffusion model choice process must exhibit the following properties: 1) its level of activity in each trial at the time of choice should correlate with the total level of activity predicted by the best-fitting drift-diffusion model; 2) it should receive as an input the computations of the area of the ventromedial prefrontal cortex associated

with computing decision values; and 3) it should modulate activity in the motor cortex in a way that is consistent with implementing the choice.<sup>9</sup> They found that activity in two parts of the brain—the dorsomedial prefrontal cortex and the bilateral intraparietal sulcus—satisfied the three required properties and thus was consistent with the implementation of the drift-diffusion model.

#### **4. Decision values are computed by integrating information about the attributes associated with each option and their attractiveness.**

From a physiological perspective, even the simplest of choices involves a bundle of multiple attributes. For example, eating an apple has implications for basic dimensions such as taste, caloric intake, vitamin and mineral regulation, as well as more abstract dimensions such as health or self-image. Let  $d_i(x)$  denote the characteristics of option  $x$  for dimension  $i$ . The model assumes that

$$v(x) = \sum w_i d_i(x),$$

for some set of weights  $w_i$ .

Consider several aspects of this assumption. First, the decision values used to guide choices depend on the attributes that are computed for each option at the time of choice. This implies that the decision value signals, and thus the choice process, take into account the value of an attribute only to the extent that the brain can take it into account in the construction of the decision values. Second, it provides a source of preference heterogeneity across individuals: some people might fail to incorporate a particular dimension in the decision values, not because they don't value it, but because they might not be able to compute it at the time of choice.<sup>10</sup>

Although much work remains to be done in testing this component of the computational model, several studies have provided supporting evidence. Hare, Camerer, and Rangel (2009) asked hungry subjects to make choices about which foods they wanted to have as a snack. Subjects were shown a variety of foods, one at a time, that varied independently in their healthiness and taste. Prior to the choice task they collected taste and health ratings for each of the foods. They found activity in the ventromedial prefrontal cortex correlated with both attributes, and that the relative weight that they received in the decision value signals of the ventromedial prefrontal cortex were correlated, across subjects, with the weight given to them in the actual choices.

<sup>9</sup> More concretely, the area involved in the comparison should increase activity in the area of the motor cortex that controls the hand movements associated with the "left" choice when the left option is chosen, and should increase activity in the area of motor cortex that controls the hand movements associated with the "right" choice when the right option is chosen.

<sup>10</sup> It is also natural to assume that experienced utility also reflects the weighted sum of the relevant attributes, with weights  $w_i^u$ , where the superscript  $u$  highlights the fact that these weights need not be the same as those used in computing decision values.

Lim, O’Doherty, and Rangel (2011b) provide an additional test of this component of the model. American-born subjects who did not speak a foreign language were asked to make choices about T-shirts with a printed word on them. The words were printed in Korean using different colors, sizes, and font sizes, and varied in meaning from the very appealing (like “love”) to the very unappealing (like “incest”). As a result, the T-shirts varied in two important dimensions: their aesthetic qualities and the semantic meaning of the words printed on them. These two specific attributes were used because previous studies have shown that the aesthetic visual properties of stimuli are computed in different areas than the semantic meaning of words. Half of the subjects were taught the meaning of the Korean words; the other half were not. This allowed the researchers to dissociate the areas associated with the computation of both attributes. In particular, they found that activity in the posterior superior temporal gyrus, which has been widely associated with the computation of semantic meaning, correlated with the value of the semantic attribute but not with the aesthetic value. The opposite was true for an area of fusiform gyrus that is known to be involved in computing the visual properties of the stimuli. In addition, activity in the ventromedial prefrontal cortex correlated with the decision values and received inputs from both areas.

##### **5. The computation and comparison of decision values is modulated by attention.**

Attention refers to the brain’s ability to vary the computational resources that are deployed in different circumstances. For example, the visual system might increase its involvement when high-value stimuli are present or when perceiving a physical threat, but might tune off in other circumstances. This ability is extremely useful because the brain’s computational resources are scarce, costly in terms of consuming energy, and in some cases might interfere with each other.

Attention can affect the choice process in two different ways. First, it might affect how attributes are computed and how they are weighted in the decision value computation. For example, the presence of other individuals might increase the brain’s likelihood to compute and weight social dimensions of the choice problem. This can be incorporated into the model as follows: Let  $a$  be a variable describing the attentional state at the time of choice. The computed decision value is then given by

$$v(x) = \sum w_i(a) d_i(x, a).$$

Second, attention can also affect how decision values are compared at the time of choice. In particular, Krajbich, Armel, and Rangel (2010) have proposed a simple variation of the drift-diffusion model in which the evolution of the relative decision value signal depends on the pattern of attention. The model is identical to the basic drift-diffusion set-up except that the path of the integration at any particular instant now depends on which option is being attended to. Thus, for example, when the  $x$  option is being attended, the relative decision value signal evolves according to

$$R_{t+1} = R_t + \theta \times (\beta v(x) - v(y)) + \varepsilon_t,$$

where  $\beta$  measures the attentional bias towards the attended option. We refer to this model as the “attention drift-diffusion model.” If  $\beta = 1$ , the model is identical to the basic model and choice is independent of attention, but if  $\beta > 1$ , choices are biased towards the option that is attended longer.

Two properties of the model are worth highlighting. First, it predicts that exogenous changes in attention (for example, through experimental or marketing manipulations) should bias choices in favor of the most attended option when its value is positive, but it should have the opposite effect when the value is negative. Second, the model makes strong quantitative predictions about the correlation between attention, choices, and reaction times—predictions that can be tested using eye-tracking.

The assumptions that the computation and comparison of decision values are modulated by attention have been explicitly tested. With respect to the computation of decision values, Hare, Malmoud, and Rangel (2011) used a paradigm similar to the “health–taste” food choice task described above to investigate the extent to which the decision value computations in the ventromedial prefrontal cortex that reflected the health and tastiness of the foods could be externally manipulated. In particular, they asked subjects to make food choices in one of three conditions: pay attention to health considerations, pay attention to taste considerations, or—in a control condition—to react naturally. It was emphasized that subjects should make choices based on their preferences and should pay equal attention in any of the situations. They found that the healthiness of the choices, as well as the extent to which health was reflected in the ventromedial prefrontal cortex value signals, increased in the health attention condition. Furthermore, the extent to which the impact of the health-attention instruction affected behavior was correlated, across subjects, with the extent to which it affected the weight that health attributes received in ventromedial prefrontal cortex signals.

With respect to the comparison of decision values, Krajbich, Armel, and Rangel (2010) used eye-tracking to test the predictions of the attention version of the drift-diffusion model. They found that this model is able to generate a surprisingly accurate quantitative account of the strong predictions of the model. They also found evidence for a substantial attention bias in the choice process: options that were fixated on more, due to random fluctuations in attention, were more likely to be chosen. In follow-up work, Krajbich and Rangel (2011) have shown that a natural extension of the attention version of the drift-diffusion model to the case of three-way choice also provides a very good quantitative fit of data.<sup>11</sup> A central prediction of the attention version of the drift-diffusion model is that exogenous increases

<sup>11</sup> Interestingly, the authors show that the three-way choice data can be explained quantitatively using the parameters estimated from the binary choice case. This finding suggests that the underlying processes might be robust for small numbers of items.

in the amount of relative attention paid to an appetitive item should increase the probability that it is chosen. Consistent with this prediction, several studies have found that it is possible to bias choices through exogenous manipulations of visual attention (Armel, Beaumel, and Rangel, 2008; Milosavljevic, Malmaud, Huth, Koch, and Rangel, 2010; Shimojo, Simion, Shimojo, and Scheier, 2003).<sup>12</sup>

## **Economic Implications of the Neuroeconomic Model of Simple Choice**

### **Prevalent and Systematic Mistakes in Economic Choice**

One important implication of the neuroeconomic model of simple choice is that individuals can often make mistakes. In this framework, an optimal choice is made when the option associated with the largest experienced utility signal at consumption is selected, and a mistake is made otherwise. There are three potential sources of mistakes: 1) stochastic errors in choices that are embodied in the drift-diffusion model; 2) errors in the computation of decision values, perhaps by systematically failing to take into account some attributes that will affect experienced utility; and 3) biases due to how attention is deployed in the computation of decision values, or in the weight that they receive in the comparison process.

Note that the model goes beyond simply pointing out that mistakes are likely and provides insights into how economic variables, like the opportunity cost of time or marketing interventions, can affect the probability of mistakes. An important open question is how large the potential mistakes in various domains are. Preliminary experimental evidence suggests that as many as 20 percent of simple choices might be mistakes, although it is likely that the proportion of mistakes changes with details of the choice situation, such as stakes or cognitive load (Frydman, Camerer, Bossaerts, and Rangel, 2011; Krajbich, Armel, and Rangel, 2010; Milosavljevic, Koch, and Rangel, forthcoming).

An implication of the model is that one cannot use simple versions of revealed preference to measure welfare and that more sophisticated procedures that take these mistakes into account must be developed. This insight provides a neurobiological motivation for the field of behavioral welfare economics. For example, Bernheim and Rangel (2009) have proposed a modified revealed preference procedure that makes it possible to measure experienced utility from the choice data even when mistakes are possible. A critical component of their methodology is the identification of “suspect” choice situations in which there is reason to believe

<sup>12</sup> Lim, O’Doherty, and Rangel (2011a) have used fMRI to test if some of the computations necessary to implement the attentional drift-diffusion model are encoded in the brain. Note, in particular, that in this model, choices are made by adding over time the instantaneous attentionally modulated relative value signal given by “ $\beta v(x) - v(y)$ ”. Subjects were asked to make binary food choices while exogenously controlling their visual fixations, which is a natural way of manipulating attention. Consistent with this component of the model, they found that the area of ventromedial prefrontal cortex associated with decision values also computed an attentionally modulated value difference.

that the subject might have made a mistake. (For related work, see Rubinstein and Salant, 2006; Salant and Rubinstein, 2007).

It is important to emphasize a methodological aspect of how neuroeconomics deals with mistakes. Since measuring the experienced utility associated with particular consumption episodes using neurometric methods is still very difficult, it is not possible to test the presence of decision-making mistakes directly. However, a roundabout approach is possible. Suppose that systematic tests of the model using neuroeconomic methods establish its validity. Then, the presence of mistakes and their relationship to different model components follows directly from the fact that the choices are made using these specific processes. In other words, once the computational processes are pinned down, their implications are also likely to be valid, even if they are hard to test directly.

### **Neural Foundations for Random Utility Models**

Although the basic economic theory of revealed preference is based on the assumption of a stable and nonstochastic choice correspondence from choices to observable variables, empirical economists know that randomness is a fact of life. This motivated the development of random utility models of choice, which are a cornerstone of empirical research (Gul and Pesendorfer, 2010, 2006; Luce, 1959; McFadden, 1974, 2005). The computational model based on the drift-diffusion model makes behavioral predictions that are highly consistent with random utility models. Thus, the neuroeconomic model provides a neurobiological foundation for random utility models. However, the two models have one important difference. In the drift-diffusion model, the noise arises during the process of comparing the computed decision values, and thus it does not reflect changes in underlying preferences: it is purely computational or process noise. In contrast, random utility models assume stochastic shocks to the underlying preferences. This difference is important, because the two models will make different normative predictions about the quality of choices.

The computational model also makes predictions about how contextual and environmental variables should affect the amount of noise in the choice process. For example, Milosavljevic, Malmaud, Huth, Koch, and Rangel (2010) asked subjects to make simple food choices with and without time pressure, and found that time pressure speeded up the decisions but also led to noisier choices. Critically, they also found that the differences between both conditions were explained with high quantitative accuracy by a single change in the drift-diffusion model parameters: the barriers of the drift-diffusion model (as illustrated in Figure 1) were smaller under time pressure. Since many economic factors affect the opportunity cost of time, this model predicts that the quality of decision making should change with such factors. It also provides a mechanism for why subjects might make fewer mistakes when the stakes are sufficiently high: in those cases, subjects might increase the size of the barriers significantly in order to slow the choice process and reduce mistakes.

### **“Wired” Restrictions in the Choice Correspondence**

The viewpoint that simple economic choices are made by computing decision values and comparing them using the drift-diffusion model implies that knowledge about the systems involved in the computation of decision values provides important clues about the structure of the choice correspondences—that is, how individual choices will be affected by the observable characteristics of the situation. For example, if we know that the decision values are wired to be unresponsive to a certain variable, then we know that choices cannot depend on that variable.

Consider an illuminating example: Padoa-Schioppa has used single neuron recordings in monkeys to investigate the extent to which the decision values assigned to a particular option in ventromedial prefrontal cortex neurons depend on other options in the choice set (Padoa-Schioppa, 2009; Padoa-Schioppa and Assad, 2006, 2008). In this setting, animals make binary choices between different amounts and types of juices. The range of decision values that animals need to compute is held constant in some experiments but varied systematically in others. One key finding of these studies is that the decision value signals exhibit “range adaptation”: the best and worst items receive the same decision value, regardless of their absolute attractiveness, and the decision value of intermediate items is given by their relative location in the scale. This finding matters for economics because it implies that the likelihood and size of decision mistakes increases with the range of values that needs to be encoded. It also means that the probabilistic choice correspondence fails to satisfy Independence of Irrelevant Alternatives, a finding at odds with the assumptions of many popular random utility models (for example, Gul and Pesendorfer, 2006; Luce, 1959).

### **Attention, Marketing, and Behavioral Public Policy**

In the neuroeconomic model, exogenous shifts in attention can bias choices in systematic ways. In particular, cues and frames that direct attention towards certain attributes should increase the weight that they receive in the computation of decision values, and thus in choice. This provides a neurobiological foundation for the effectiveness of some marketing and behavioral public policies.

As one example, many marketing interventions are centered on changing the visual saliency and attractiveness of packages. Milosavljevic, Malmaud, Huth, Koch, and Rangel (2010) tested the effectiveness of these types of interventions using a binary choice paradigm in which they varied the relative “visual contrast” of the images of the options. They found that this manipulation had a sizable effect in attention paid and that it biased the choices as predicted. A critical question for future research is to understand how these marketing techniques interact with traditional economic variables such as price and familiarity.

As another example, the neuroeconomic model suggests that environmental cues that direct attention towards the long-term features of the stimuli—like health in the case of food or smoking—may lead to healthier decisions. An example of this class of policies is the mandatory placement of pictures on cigarette containers

depicting, in highly emotional form, the long-term consequences of smoking. These policies are associated with higher indicators of smoking cessation than less-salient text warnings that convey similar information but may be less effective in capturing attention (Borland et al., 2009; White, Webster, and Wakefield, 2008). The neuroeconomic model proposed here readily explains this phenomenon: the pictures decrease the decision value of cigarettes because they increase the extent to which health considerations are taken into account in computing them.

Other candidates for how attention plays a critical role in economic choice include cultural norms that affect memory retrieval and cognitive patterns; educational interventions that have a similar effect; and many of the “nudge” or “libertarian paternalistic” policies that have been advocated by behavioral economists (Bernheim and Rangel, 2004, 2007; Kling, Congdon, and Mullainathan, 2011; Thaler and Sunstein, 2003, 2008). Indeed, psychological and behavioral economics research has identified a large and diverse set of noneconomic factors—framing effects, attention effects, saliency effects, subliminal primes—that affect choice behavior. Unfortunately, to date, economics lacks a model capable of providing a unifying account of these effects. A natural hypothesis, admittedly a speculative one at this point, is that many of these phenomena might operate by changing how decision values are computed through attentional effects.

### **Novel Insights about Experienced Utility**

Psychologists and behavioral economists have speculated that experienced utility—that is, subjective well-being—might be modulated by variables that are not traditionally considered to be sources of well-being, like the extent to which consumption was anticipated, the price at which the item was purchased, and beliefs about the properties of the stimulus being consumed. For example, pain stimulation experiments have manipulated subjects’ beliefs about the strength of the electric shocks given to the subjects and have found that the beliefs modulate reports of experienced pain as well as activity in areas that are known to correlate with subjective pain reports. Some behavioral economics models incorporating these types of assumptions have been proposed (Koszegi and Rabin, 2006, 2009, 2007). Although these models make testable behavioral implications, it is often difficult to disentangle them from competing explanations using only choice data.

Neuroeconomic methods provide an alternative methodology to address this problem: measure neural activity in areas that are known to encode experienced utility and test the extent to which the hypothesized effects are present. This research program has already shown that experienced utility can be modulated by surprise, prices, and beliefs (Bushong, Rabin, Camerer, and Rangel, 2011; de Araujo, Rolls, Kringelbach, Velazco, Margot, and Cayeux, 2005; McClure, Li, Tomlin, Cypert, Montague, and Montague, 2004; Nitschke et al., 2006; Plassmann, O’Doherty, Shiv, and Rangel, 2008). It is likely that similar experiments will identify other important sources of experienced utility in the future. An important caveat for this research program, emphasized by Bernheim (2009a), is that equating economic well-being



with the experienced utility signals computed at a particular instant is an approximately valid assumption in the simple choice context but not in the case of more complex choices that have consequences over extended periods of time.

### **De Gustibus Est Disputandum**

Many economists view preferences as exogenously given features of an economic model. Economics does not yet have a satisfactory theory of where preferences come from or how they might be modulated by other economic variables. The neuroeconomic approach provides novel potential explanations. Consider an example: because decision values depend on how individuals compute and weight different attributes, people may make selfish choices not because they do not care about others, but because it is hard for them to understand another's perspective. This hypothesis makes the prediction that subjects will behave more altruistically if the necessary information is exogenously provided by other people or by institutions.

Hare, Shultz, Camerer, O'Doherty, and Rangel (forthcoming) provide evidence directly related to this issue. They found with fMRI evidence that subjects who donate more to charities activate more strongly the posterior temporal sulcus at the time of choice and that the responses in this area modulate activity in the areas of ventromedial prefrontal cortex that compute decision values. The posterior temporal sulcus has been shown to play a critical role in characterizing the mental states of others (Saxe and Kanwisher, 2003; Saxe and Wexler, 2005). This finding suggests that the posterior temporal sulcus might be important for some types of social choices because it computes information about the perceived need of others that is passed to the ventromedial prefrontal cortex to compute the decision value of giving. In addition, there is significant individual variation in the ability to assess another's state of mind. This suggests that some of the observed individual differences in the amount of altruism might be due to cognitive limitations and not to the absence of an altruistic component in experienced utility.

### **More Complex Decisions: Self Control, Social Preferences, and Norm Compliance**

Examples of more complex choices include intertemporal choices involving monetary or pleasure–health tradeoffs; financial decisions in complex environments such as the stock market; choices involving social preferences; and compliance with prevailing social norms. An active research agenda in neuroeconomics is devoted to characterizing how the mechanisms at work in simple choice change in these more complex situations and which additional processes come into play. Not surprisingly, given that these are the early days of the field and the fact that these domains are significantly more complicated, it is not possible yet to provide full computational models of complex choice. Nevertheless, as we discussed here, some existing results have implications that should be of special interest to economists.

### **Intertemporal Choice**

Here we illustrate how the neuroeconomics literature is attacking the problem of complex choice by focusing on the problem of intertemporal choices. In the basic version of the problem, individuals choose between two options,  $x$  and  $y$ , in the present, and their choices have consequences on multiple dimensions for extended periods of time.

A basic question is how the computational model describing intertemporal choices might differ from the one described above for simple choices. To a large extent, the existent evidence suggests that all of the key components of the model for simple choice are also at work here: choices are made by assigning decision values to each option at the time of choice; these decision values are computed by identifying and weighting attributes; decision values are compared using a drift-diffusion model; and all of these processes are modulated by attention.

With respect to the computation of decision values, several empirical studies have shown that the same areas of ventromedial prefrontal cortex that encode them in simple choices also do so in more complex situations involving dietary choices (Hare, Malmoud, and Rangel, 2011; Hare, Camerer, and Rangel, 2009; Hutcherson, Plassmann, Gross, and Rangel, 2011) and intertemporal monetary choices (Kable and Glimcher, 2007; McClure, Laibson, Loewenstein, and Cohen, 2004; McClure, Ericson, Laibson, Loewenstein, and Cohen, 2007). Interestingly, the decision values based on ventromedial prefrontal cortex activity do not depend on the extent to which the subjects act virtuously. For example, in Hare, Camerer, and Rangel (2009), activity in the ventromedial prefrontal cortex correlates with the decision values equally well in good and bad dieters, and in Kable and Glimcher (2007) the correlation does not depend on the extent to which delayed payoffs are discounted.

In intertemporal choice, the decision values seem to continue to be based on a weighted sum of attributes, but the attributes all need to be time-dated, and attributes can have different weights at different times (which allows for time-discounting in the weighting of attributes). The dietary choice study of Hare, Camerer, and Rangel (2009) discussed above suggests decision values are computed by integrating the value of attributes over dimensions and time. (Recall that hungry subjects were asked to make food choices about which foods they wanted to eat, foods that varied in their health and taste properties.) Consistent with this assumption, they found that activity in the ventromedial prefrontal cortex correlated with both attributes and that the relative weight that they received in the ventromedial prefrontal cortex decision value signals was correlated, across subjects, with the weight given to them in the actual choices. In addition, their follow-up study (Hare, Malmoud, and Rangel, 2011), also discussed above, in which subjects were asked to pay attention to either the health or taste attributes, shows that attention modulates the integration of the attributes into the decision values.

The assumption that the decision value is based on a sum of attributes weighted over time raises questions about whether the brain makes such a computation for

all attributes at all times. A working assumption is that the grid of attributes and time horizons can be partitioned into two sets: those attributes at given times that are easily computed, and those attributes at given times that are considered only if cognitive effort is deployed. Of course, a critical question is what determines which attributes belong in which set.

Psychological experiments provide some useful hints. For example, it is plausible that when an attribute occurs sooner in time, it is more likely to be taken into account. This is suggested, but not fully established, by the multitude of animal and human experiments showing a strong present bias in intertemporal choice (for a review, see Frederick, Lowenstein, and O'Donoghue, 2002). However, this type of behavioral evidence is not definitive for our present purposes because it cannot distinguish between when an attribute (say, in the more distant future) is computed but receives a low weight, and a case in which it is not considered at all. A series of classic experiments by psychologist Walter Mischel suggest that physical proximity is also a key determinant (for example, see Metcalfe and Mischel, 1999; Mischel and Moore, 1973). In particular, Mischel investigated children's ability to postpone consumption of candy in order to get more candy and found that their ability to wait was substantially increased if the items were not present or if they were present but covered. Furthermore, based on the behavioral evidence, psychologists have repeatedly proposed that emotional factors, such as "taste now," are more likely to be considered than less emotional ones, such as "health later" (Liberman and Trope, 2008; Metcalfe and Mischel, 1999).

The experiment by Hare, Camerer, and Rangel (2009) carried out the first neurobiological test of this hypothesis. The logic of their test goes as follows. Based on the behavioral data, they were able to divide their sample into two groups: self-controllers, who assigned above-average weight to the health attributes, and non-self-controllers, who assigned below-average weights to health attributes. They then hypothesize that activity in areas of the dorsolateral prefrontal cortex that have been shown to be involved in implementing the type of scarce cognitive processes described above should be more active at the time of choice in the self-control than in the non-self-control group. Furthermore, it should be the case that these dorsolateral prefrontal cortex areas modulate activity in the ventromedial prefrontal cortex so that they can influence the decision values that are computed. They found evidence consistent with this hypothesis. Furthermore, the dorsolateral prefrontal cortex modulated the ventromedial prefrontal cortex decision value signals in the self-control group but not in the non-self-control group.

### **The Problem of Experienced Utility in Intertemporal Choice**

In simple choice, it is natural to think of the experienced utility signal at the time of consumption as a neurobiological marker of welfare, because the objects of choice in that case (such as listening to music or sipping a drink) have immediate physiological and hedonic consequences at the time of consumption, but a minimal impact later on. Things are significantly more complicated in the case of intertemporal choice since decisions have hedonic consequences over extended

periods of time (for example, eating an unhealthy cake affects health for indefinite future). This implies that experienced utility at each instant depends on the entire history of choices and not on a single consumption episode. As a result, it is difficult to measure how specific choices affect the experienced utility signals at future times.

No theoretical or empirical study has persuasively addressed how to find a neuroeconomic marker for measuring experienced utility in an intertemporal context. As a result, it is virtually impossible to test directly for the presence of mistakes in the intertemporal choice case. Fortunately, there is a conceptual work-around for this problem. In the absence of sound measures of experienced utility, it is virtually impossible to test directly for the presence of mistakes. However, it is still possible to use neuroeconomic methods to construct and empirically validate a computational model of the underlying computational processes. Once we are confident that the model provides a sufficiently good description of the forces at work, we can conclude that other properties implied by the model are also likely to hold, including the presence of decision mistakes in certain circumstances.

### **Competing Decision Systems in Complex Choice**

A growing body of work suggests that besides the decision-making processes discussed previously, the brain sometimes uses other systems, like the Pavlovian system or the habitual control system (Balleine, 2005; Balleine, Daw, and O’Doherty, 2008; Daw, Niv, and Dayan, 2005; Rangel, Camerer, and Montague, 2008). The Pavlovian controller is activated by stimuli that activate automatic “approach or avoid” behaviors. A typical example is the common tendency to move quickly away from stimuli such as snakes and spiders. In contrast to the systems described in this paper, which can be used to solve many decision problems, the Pavlovian controller is thought to work only in a relatively small number of evolutionarily “hard-wired” circumstances. Those circumstances may sometimes also apply to economic choices—like food choices when the food stimuli are present at a buffet table. For example, Bushong, King, Camerer, and Rangel (2010) showed that Pavlovian forces can have a sizable impact in such choices.

The habitual system is more flexible than the Pavlovian system and less flexible than the goal-directed one. In particular, the habitual system learns to promote actions that have repeatedly generated high levels of experienced utility in the past over those that have generated lower levels. However, it is computationally much less sophisticated than the goal-directed system: it makes “choices” over actions but not stimuli, and it can only do so in domains in which it has sufficient experience. These circumstances might apply to some economic choices, like which road to travel during a commute, or addiction, but not to others.

The goal-directed control system described in this paper may sometimes be in conflict with the prepotent (that is, latent) responses driven by the Pavlovian and the habitual system, and, depending on people’s ability to deploy cognitive resources to control the prepotent response, the goal-directed system may or may

not prevail. It is widely believed that neural activity in the lateral prefrontal cortex plays a key role in the ability to deploy these cognitive resources.

Knoch, Pascual-Leone, Meyer, Treyer, and Fehr (2006), Knoch, Schneider, Schunk, Hohmann, and Fehr (2009), Baumgartner, Knoch, Hotz, Eisenegger, and Fehr (forthcoming), and Figner et al. (2010) provide causal evidence related to this issue in various types of complex decisions. They down-regulate neural activity by applying transcranial magnetic stimulation of a subject's dorsolateral prefrontal cortex, which is hypothesized to be involved in the cognitive control of prepotent responses such as the impulse to behave selfishly or to grab a sooner, smaller reward instead of waiting for a later, larger reward. In Knoch, Schneider, Schunk, Hohmann, and Fehr (2009), the neural down-regulation of dorsolateral prefrontal cortex induces subjects to cheat their partner in a repeated trust game although they know that this decreases the future trust of their partners. In other words, subjects forgo the long-run gains from acquiring a reputation as a trustworthy trading partner in favor of the short-run gains from cheating. In Figner et al. (2010), the down-regulation of dorsolateral prefrontal cortex caused more impatient choices in an intertemporal choice task. In Knoch, Pascual-Leone, Meyer, Treyer, and Fehr (2006) the neural down-regulation of dorsolateral prefrontal cortex causes a large decrease in responders' willingness to reject unfair offers in the ultimatum game although responders still judge low offers as very unfair. As in Knoch, Schneider, Schunk, Hohmann, and Fehr (2009), choices are again biased in the direction of more selfish behavior. In addition, in Baumgartner, Knoch, Hotz, Eisenegger, and Fehr (forthcoming) the down-regulation of dorsolateral prefrontal cortex also leads to a down-regulation of the decision value of rejecting an unfair offer in the ventromedial prefrontal cortex and largely removes the neural connectivity between these two regions.

These findings suggest that the behavioral implementation of fairness goals or social norms depends on the functioning of elaborate cognitive and neural machinery that is dissociable from the knowledge of what constitutes fair or norm-compliant behavior. For example, in these experiments the subjects whose dorsolateral prefrontal cortex had been down-regulated still knew the fair thing to do, but they were significantly less likely to implement fair and norm-obedient behavior. The dissociation between the knowledge of what is fair and right from subjects' ability to behave according to what is fair and right raises difficult problems in the attribution of individual responsibility. Currently, the legal system in most Western countries holds people responsible for their norm violations if they know the social or legal norm; the above results indicate, however, that the attribution of individual responsibility can be considerably more complicated.

### **Economic Implications for Complex Choice**

The computational model outlined above provides a novel explanation for why making optimal choices in an intertemporal choice context is often difficult and why the choice could sometimes result in decision mistakes, which in psychology

are known as self-control failures. The basic idea is simple: since scarce computational processes are not always deployed correctly, and are not even available in some cases, decision mistakes can result. In this model, an individual's ability to make optimal intertemporal choices depends on the ability to deploy the cognitive control facilitated by dorsolateral prefrontal cortex processes. Moreover, a growing body of evidence suggests that other types of complex behaviors, such as norm compliance and fairness choices, also depend on these processes. Interestingly, there are several well-known sources of cross-individual variation in the activity of the dorsolateral prefrontal cortex, which lead to several implications that should be of interest to economists.

First, the cognitive control processed by the dorsolateral prefrontal cortex is impaired during stress, sleep deprivation, or intoxication, and it is depleted in the short term with repeated use. This predicts that subjects are more likely to make short-sighted decisions under stress, tiredness, or drunkenness, or after having made several previous choices requiring cognitive control. This last prediction is well-known from social psychology experiments (Baumeister, Bratslavsky, Muraven, and Tice, 1998; Baumeister and Vohs, 2004; Muraven and Baumeister, 2000; Muraven, Tice, and Baumeister, 1998; Vohs, Baumeister, Schmeichel, Twenge, Nelson, and Tice, 2008).

Second, the lateral prefrontal cortex is the last area of the brain to mature fully, often only when people age into their mid-20s (Casey, Galvan, and Hare, 2005; Casey, Jones, and Hare, 2008; Giedd et al., 1999; Sowell, Thompson, Holmes, Jernigan, and Toga, 1999; Sowell, Thompson, Tessner, and Toga, 2001; Sowell, Peterson, Thompson, Welcome, Henkenius, and Toga, 2003). As a result, the model predicts the well-known fact that children and teenagers exhibit lower self-control and norm compliance levels.

Third, and more speculatively, the areas of dorsolateral prefrontal cortex identified in these studies have also been shown to play a role in cognitive processes such as working memory. This finding raises the intriguing possibility that an individual's ability to postpone gratification might be affected by cognitive abilities. Two recent studies provide evidence in support of this hypothesis. Shamosh et al. (2008) measured intelligence; working memory span; responses of the dorsolateral prefrontal cortex during a working memory task; and discount rates in a monetary choice task. Working memory and intelligence were associated with less discounting, higher intelligence was associated with stronger responses in the dorsolateral prefrontal cortex, and these stronger responses were associated with lower discounting. Even more intriguingly, Bickel, Yi, Landes, Hill, and Baxter (2011) have shown that working memory training reduces discounting in a monetary choice task. This suggests that there might be a causal relationship between cognitive abilities, such as working memory capacity and intelligence, and the ability to exert self-control. As a result, this might provide a neurobiological link for why educational interventions and parenting might affect adult economic performance (Heckman, 2006).

## Final Remarks

Neuroeconomics is a nascent field. Much of the basic work remains to be done, and many of the details of the computational models of choice described here are likely to change and evolve over time. However, we hope that this description of the current frontier of neuroeconomics convinces economists that a great deal has already been learned about how the brains make choices, and that these findings already provide insights that are useful in advancing our understanding of economic behavior in many domains. We also hope that this paper helps to shift the heated debate about the usefulness of neuroeconomics research for economics from the abstract and methodological (as in Bernheim, 2009b; Camerer, Loewenstein, and Prelec, 2005; Gul and Pesendorfer, forthcoming) to the concrete; in our view, productive future debates should center on the validity of specific computational models and their implications for modeling economic behavior.

We conclude the paper by emphasizing some of the prominent questions that are yet to be resolved: What is a good computational model of experienced utility and well-being in complex settings where choices have consequences over extended periods of time? Are there more complex economic choices in which some of the processes identified in the case of simple choice break down? What is the range of attributes computed by the brain at the time of choice and how are they integrated into the decision value signals? What determines how attention is deployed? How are values and attributes learned over time and over the lifecycle? Are there alternative behavioral controllers that influence choices in some domains? The answer to these questions will provide a much deeper mechanistic understanding of choice, including the circumstances and factors that drive choice mistakes, and their positive and normative implications.

Clearly, much remains to be learnt. May we live in interesting times!

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