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How can neuroscience inform economics?

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Neuroeconomics is now a well-established discipline at the intersection of neuroscience, psychology and economics, yet its influence on mainstream economics has been smaller than on the other two fields. This is in part because, unlike neuroscientists and psychologists, most economists are not interested in the process of decision making *per se*. We argue that neuroscience is most likely to influence economics in the short run by providing new insights into the relationships between variables that economists already study. In recent years the field has made many such contributions, using models from cognitive neuroscience to better explain choice behavior. Here we review the work that we think has great promise to contribute to economics in the near future.

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Introduction

Since its inception, the field of neuroeconomics has generated debate about when and how neuroscience can be used to inform the study of economics. Early articles outlined the exciting possibilities that cognitive neuroscience affords economists, with its huge amount of data and know-how regarding the processes of decision making [1]. A subsequent backlash questioned the value of using neuroscientific data to test models of economic choice [2]. A large body of ensuing work has taken more nuanced views, debating the pros and cons outlined in these seminal articles (e.g. [3,4•,5,6]). In this article we provide a selective survey of some of the recent directions in the field that we consider most likely to be of interest to mainstream economists in the near future. Note that by neuroeconomics we mean the study of data that shed light on the biological processes underlying economic choice, including reaction times, eye tracking, electroencephalography (EEG) and functional magnetic resonance imaging (fMRI).

In discussing the potential benefits of neuroscience for economics, we will largely allow the economics profession to 'set the rules', that is, to define the relationships which they hope to understand. Using the formulation of Bernheim [3] and Dean [5], we think of the economist as interested in developing models which define the relationship between some environmental parameters X and a set of economic behaviors Y. Such a model would take the form of a function $f: X \rightarrow Y$ which describes what behavior will occur in each possible environment. The fact that some underlying process, possibly mediated by some intermediate variables Z, governs this behavior is not of direct interest to the economist. So, for example, the fact that f is the composite of two functions, $h_1 : X \rightarrow Z$ and $h_2 : Z \rightarrow Y$, is not necessarily interesting to the economist: understanding h_1 and h_2 is useful only insofar as it helps to construct a better f. To take a concrete example, the act of choosing an alternative ($y \in Y$) from a budget set ($x \in X$) may in fact be the result of first a decision about which available alternatives to look at ($z \in Z$), and a subsequent choice from those considered alternatives. However, the economist is interested only in understanding the relationship between budget sets and choice — perhaps because data on what is looked at is not typically available to them in the situations they are keen to model. We take as given that the relationship between X and Y is not fully understood: once f is known, understanding the intermediate processes may no longer be of any use to the economist. The question then is what is the most efficient way to pursue the, as yet unknown, f?

In principle there are many ways in which understanding the process of choice could help economists to model the relationships they are interested in [3,4•,5]. The most widely accepted approach is inspiration: if a researcher discovers the form of h_1 and h_2, this implies a functional form for f which may constitute a new model that had not previously been considered. Observation of intermediate variables Z can also allow the researcher to 'break up the problem', and so test models of h_1 and h_2 separately, rather than model the composite function f: it may, for example, be easier to separately model the process which determines what is looked at, and the process of what is chosen conditional on what is looked at, rather than trying to model process of choice in one go. More controversially [3], data on intermediate processes has been used to test existing models of economic choice.

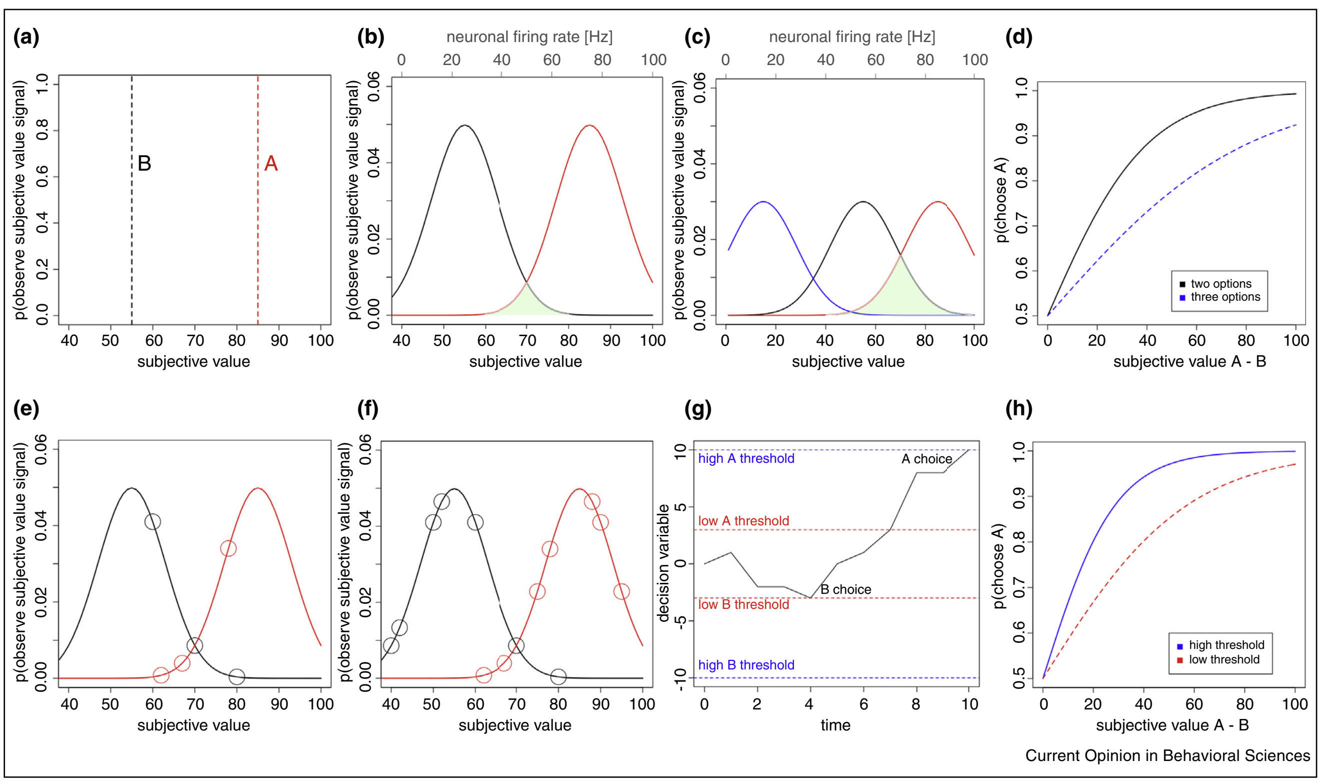
Rather than add to the large existing literature on the in-principle value of neuroeconomics, we present a selective survey of the current research in neuroscience that we believe may have implications for research in economics. These are mainly cases of 'inspiration' in which an understanding of neuroscience suggests new models relating variables that are of *a priori* interest to economists. We highlight the features of these research agendas that make them particularly likely to be relevant to economists.

The biological causes of stochastic choice

Perhaps the most fundamental relationship of interest to economists is that between the set of available alternatives and the choice made from that set: for example, what bundle of goods a shopper will choose in a supermarket, how much money a worker will save from their paycheck, or whether a young adult will choose to join the labor force or stay on in education.

The classic model of economic choice is one of deterministic preference maximization (Figure 1a). However, it has long been recognized that people tend to exhibit choices that are not internally consistent, and may appear stochastic: in two seemingly identical choice situations the same person may select different alternatives. Economists have developed models of stochastic choice based either on the concept of random fluctuations in utility, or choice errors (e.g. [7]). A standard approach is to employ either the logit or probit discrete choice models, which

Figure 1



Processes leading to stochastic choice. **(a)** Traditional economic choice models assume that people know their preferences so when choosing between two options A and B, one must simply compare the known subjective values and pick the higher one, in this case A. **(b)** Instead, people have noisy representations of these subjective values, encoded in neuronal firing rates. At any instant, the individual can receive value signals from the neuron(s) encoding A and B and compare them. The probability of receiving different signals is given (for example) by these probability distributions. If there is overlap of the distributions then there is some probability that the decision maker receives signals that lead him to make the incorrect choice, in this case B. **(c)** When a third, irrelevant option is added to the choice set, the range of subjective values expands, while the range of neuronal firing rates remains constant (with constant noise). Thus the same range of firing rates must cover a larger value range. This produces more overlap of the signal distributions for A and B (green shaded area), leading to an increased likelihood of error. **(d)** The black curve represents a standard logistic choice curve between A and B, without the presence of C. The blue dashed curve represents a choice curve of the probability of choosing A over B that results from the addition of C, with normalization. The presence of C increases the likelihood of error and thus flattens the choice curve. **(e,f)** In order to reduce errors, the decision maker may accumulate a few (e) or many (f) samples and compare the net evidence. How many samples the decision maker collects will depend on his/her cost of time and benefit from making the right choice. **(g)** A sequential sampling model (SSM) representation of how this net evidence is accumulated up to either a low threshold (as in (e)) or a high threshold (as in (f)). Once the decision variable reaches a predefined threshold, the decision maker stops collecting evidence and makes a decision. Higher thresholds require more time but lead to more accurate responses, as seen in **(h)**. Here we again see two choice curves for A over B, one (in blue) resulting from a high threshold, and one (dashed in red) resulting from a low threshold.

specify highly constrained choice distributions based on the underlying preferences. These models are widely used within economics. However, they often perform poorly empirically [8,9•]: as noted by Woodford [10], 'there is no obvious reason to expect that the additive random terms in people's valuations...should be drawn from this particular type of distribution, so that there is little reason to expect logistic regressions to be correctly specified...'. Such misspecification can lead to incorrect predictions and mistaken inference about the underlying preferences.

Recent work in neuroscience, psychology and neuroeconomics has begun to identify some of the mechanisms underlying the process of decision making, and why these processes might lead to stochasticity in choice. This work has identified new classes of stochastic choice models, linking the set of available alternatives and the resulting distribution of choice.

One set of models is based on the observation that choices are implemented in the brain by comparing firing rates of neurons favoring each alternative. The inherent variability in these firing rates means that subjective value, and thus preference, is represented imprecisely. Furthermore, these firing rates are constrained to a finite range (∼0–200 Hz). This means that if the same neurons are to be efficiently used to compare (say) two different cars and also two different types of coffee, then this finite range of firing rates must be adapted to cover the range of values represented by the currently available options. This is commonly referred to as 'adaptive coding' or 'normalization'. Assuming that there is some fixed variability in firing rate of these neurons, this implies that the imprecision of subjective value estimates will increase as the range of values in the choice environment expands. Thus the discriminability of two choice options is a function of the range of values across available options (Figure 1b–d) [11,12•,13•]. An alternative, divisive normalization model, instead uses the sum of the value inputs as a normalization factor [14].

While there is disagreement about how exactly normalization occurs, both procedures give rise to novel models: an understanding of the link between valuation and neural representation (h_1) and neural representation and choice (h_2) has led to new models of stochastic choice (f). Both normalization models predict specific failures of the stochastic version of the independence of irrelevant alternatives (IIA), which states that the relative probability of choosing between two alternatives should be unaffected by what else is available. IIA is a fundamental implication of the logit choice model. Moreover, both models have been shown to accurately predict the distribution of choices in different contexts. The process of normalization may help economists to understand the impact of unchosen alternatives on choice probabilities, for example, as demonstrated by decoy effects [15•].

A second class of models is based on the observation that information (i.e. evidence), encoded in stochastic neuronal activity, is accumulated over time until the decision maker is confident enough to make a decision. Data to support this idea have been around for over a century and sequential sampling models (SSM) are ubiquitous in psychology and neuroscience [16–19]. Recent work has used a combination of reaction times, eye tracking, and data on brain activity to establish that economic choices do indeed conform to the predictions of SSMs [19–22,23•,24–26,27•]. These models provide a clear advantage over traditional static decision models (such as logit), not simply because they capture non-choice data (which an economist may not care about), but because they imply new choice functions, which can predict the relationship between stochasticity and time constraints, opportunity costs, variations in choice difficulty, etc. [10]. SSMs give rise to stochastic choice models, which are a subset of the class of random utility models, some of which are distinct from logit and probit (Figure 1e–h). There is good evidence that SSMs outperform standard logit models at predicting economic choice [8]. Furthermore, Webb [9•] demonstrates how using a non-SSM stochastic choice model can result in mis-estimation of underlying preferences, for example, attitude to risk.

Going a step further, there is growing evidence that most economic choice is carried out by the same functional units in the brain [28••]. This implies a common set of computations across different domains that have traditionally been modeled independently (e.g. risk preferences, time preferences, and social preferences), thus potentially allowing for prediction of behavior in one domain based on fits to behavior in another domain [29•]

The costs of attention

Behavioral economists have recently started to explore models in which information acquisition from the decision-making environment occurs endogenously: the amount and type of information gathered is chosen to maximize the benefit derived from subsequent choice, minus the cost of information. These models of 'rational inattention' have been applied to a number of economic problems (e.g. [30–32]). A key ingredient to these models is the cognitive cost of acquiring information. Unfortunately, such costs are not generally well understood, and the precise form of the cost function can have an important impact on predicted economic behavior [33]. One approach is to treat these costs as unknown [34], which limits the predictive power of such models. Another is to select a particular attention cost function, usually based on Shannon mutual information — a concept borrowed from information theory, and use this to make predictions.

More recently, authors (notably [35•]) have begun to use evidence from neuroscience and psychology to try and pin down the cost of information acquisition. This work suggests that the Shannon mutual information cost function is not appropriate, and an alternative based on a different information theoretic concept — Shannon capacity — may be superior (see Box 1 for more details). One key piece of evidence comes from the work of Shaw and Shaw [36], which shows that subjects tend to allocate less attention to discriminating between events they *a priori* expect to be unlikely — in line with capacity costs but not mutual information costs. This is consistent with many perceptual phenomena and neuroscientific findings. The resulting model, when applied to economic choice, describes a number of commonly observed phenomena, including reference dependent valuation and focusing effects [11]. The fact that such behavior can be derived from an optimizing model of attentional choice gives rise to a number of novel predictions about how these effects will vary with the economic environment.

This work shows how data from neuroscience and psychology has helped to constrain the costs of attention, and therefore the relationship between available alternatives and gathered information (h_1). Coupled with a model of choice given information gathered (h_2), this gives rise to a new model of economic choice when information is costly.

Box 1 Models of rational inattention.

Economists have long recognized that information costs may lead people to ignore some potentially relevant information before making a choice. This can lead to choice 'mistakes' relative to the full information benchmark, but may still be optimal if the cost of information needed to correct these mistakes outweighs the benefits of doing so.

In order to make precise predictions it is necessary to choose a functional form for the cost function. Since the seminal work of Sims [29•], a popular choice has been for costs to be related to Shannon mutual information.

It is assumed that the decision maker wants to learn which state of the world has occurred from a possible set Ω. Their prior beliefs are given by μ. Rather than consider the specifics of a particular learning problem, the decision maker is modeled as choosing an *information structure*, which consists of a set of signals Γ, and a probabilistic mapping from states of the world to signals, with $\pi(\gamma|\omega)$ the probability of receiving signal γ in state of the world ω. While this can look rather abstract, this setup nests most models of optimal information acquisition [33]. It can also be readily applied to many of the perceptual tasks that have been studied in the psychology and psychophysics literatures by thinking of the state as the true value of some stimulus.

Sims [29•] assumed that the cost of an information structure is linear in the Shannon mutual information between states and signals.

$$I(\pi,\mu) = E_\mu\left[\log\frac{\pi(\gamma|\omega)}{P(\gamma)}\right]$$

where $P(\gamma)$ is the unconditional probability of signal γ. Mutual information, which is also equal to the expected change in entropy between prior and posterior beliefs, has several appealing properties — it can be applied to any information structure, and gives higher costs to statistically more informative information structures. It has also been justified on the basis of information theory, which relates mutual information to the expected number of bits needed to implement the information structure under particular circumstances.

One problem with mutual information, pointed out by [35•] is that, because costs are based on expectation taken at prior beliefs, it is relatively cheap to differentiate between states of the world that occur infrequently, which is incommensurate with the evidence of [36]. As a result, an alternative cost function was proposed, based on the concept of the Shannon capacity.

$$C(\pi) = \max_{\mu\in\Delta(\Omega)} I(\pi,\mu)$$

These costs are related to the bandwidth needed to support an information structure across all possible priors. As it is not a function of the actual prior beliefs, it does a much better job of qualitatively matching the data of [36], in which subjects are worse at differentiating between stimuli that occur less frequently.

Newly discovered relationships between the environment and economic choice

Recent neuroscientific research has given rise to a number of new predictions about the relationship between a person's socioeconomic environment and behavior. For example, everyone would acknowledge that nutrition is vital for a productive workforce. Yet it can have less easily anticipated effects on economic behavior. Just as nutrition affects physical development, it also affects the development of brain structure. For example, certain nutrients are critical for the maintenance of chemical balance in the brain, such as the need for the amino acids tryptophan and phenylalanine (found in most protein-heavy foods), which are key components of the neuromodulators serotonin and dopamine respectively. Decreased serotonin levels have been causally linked to many economic behaviors, including steeper temporal discounting, reduced loss aversion, and more aggression in bargaining games [37•]. Dopamine levels affect how people learn and respond to new information, as well as their risk aversion. So the specifics of what people eat, rather than simply how much they eat, can influence the brain and thus decision-making abilities [38].

There are many other environmental factors that affect the level of neuromodulators in the brain. For instance, many people deliberately manipulate their serotonin levels by taking selective serotonin reuptake inhibitors (SSRIs), as a treatment for depression. Also, patients with Parkinson's disease — which reduces dopamine levels — take L-Dopa to increase dopamine concentration in the brain, and as a result may become susceptible to pathological gambling [39]. Both neural systems also tend to deteriorate with age and so this work has implications for learning and decision making over the life cycle. Indeed, in one recent paper, L-Dopa was shown to restore reinforcement learning that had been degraded in older adults [40].

In other work, knowledge of the neural structures involved in loss aversion and strategic behavior led researchers to discover that patients with a disease leading to destruction of the amygdala are dramatically less loss-averse [41] and that across-subject variation in the volume of the temporoparietal junction (TPJ) predicts increases in altruistic behavior [42]. While variation in the structure and function of these brain regions is certainly partly genetic, there is now evidence that environment also plays a role. For instance, early-life stress has been causally linked to persistent alterations in amygdala function and behavioral impairments [43]. These examples demonstrate the potential usefulness of 'brain mapping' — ascribing various economic behaviors to processes in networks of brain regions — which has been the focus of much of the neuroeconomic literature. Early work on brain mapping focused on specific regions of the brain, while more recent work has focused more on networks of regions and how they interact. While economists may not care about the neural substrates of decision making *per se*, knowing how different parts of the brain affect economic decision making can lead to these kinds of novel discoveries.

In all of these examples, understanding of the link between environmental factors (such as consumption, disease and age) and brain function (h_1), and the link between brain function and economic choice (h_2), has suggested new models of the link between the economic environment and economic behavior.

Conclusion

The above does not provide an exhaustive list of the neuroeconomic work that may soon impact economic thinking. One further example is a vast body of literature studying the neural correlates of learning, both model-free (pure reinforcement) and model-based. While both types of learning models have been considered in the economics literature (e.g. as adaptive and rational expectations respectively), it is far from clear when people use each approach. There are now many papers using neural data to address just such a question [44,45•]. A second example is the recent work on the choice processes that emerge from optimal resource allocation in the brain [46,47]. These models assume that a central co-ordinator must allocate resources between brain systems that are responsible for different tasks. These systems care only about their own task, but also have better information than the co-ordinator as to the resources needed. A third example is the use of eye tracking to understand the way in which people make strategic decisions [48–50].

We have also taken a deliberately narrow view of the potential value of neuroeconomics by focusing on the relationships that are already of interest to economists. We have ignored the fact that the study of the neurobiology of simple decision making is itself a valuable endeavor outside of economics, and one in which neuroeconomists have made significant progress. We have also ignored the possibility that, over time, the study of intermediating processes may become a legitimate line of economic enquiry in its own right: as an analogy, because education turns out to be an important intermediary in the relationship between parental and child income, the study of the choice and impact of education is now mainstream within economics.

Furthermore, the data that economists collect is not fixed. It is instead determined by the choices made by researchers and funding bodies. As an example, the Panel Study of Income Dynamics was introduced because of the perceived need to track the economic activity of the same families over time. If it turns out that there are novel types of data that are useful in testing economic models, or in predicting economic choice, then such data may turn up more regularly in economic data sets. Response times and eye-tracking data are obvious 'gateway methods' for economists, as they have become cheaper and easier to collect as more and more economic transactions (and experiments) are conducted using computers and smart phones. The key to incorporating such measures into economics is the development of quantitative, theoretical models linking those data to choice outcomes [51,52]. The more biologically grounded the models, the more additional measures can be used to test and inform them.

Finally, one can ask whether economists might be able to use neural data to improve economic institutions. This is so far an underexplored topic. One paper made use of fMRI data to understand the causes of overbidding in auctions and then used that knowledge to reframe the auctions to increase overbidding [53]. Another paper [54] demonstrated that neural correlates of economic value could be used to supplement existing economic institutions to overcome inefficiencies caused by private information. For example, the decision about whether or not to provide a public good depends on how much each person values that good. If people are taxed based on their stated value then they will have an incentive to understate that value. This is known as the free-rider problem. It has been shown that if the public can observe a neural correlate of each person's true underlying value (e.g. using fMRI) then those 'signals' can be used to incentivize people to be truthful by rewarding them when their stated value and neural signal align . A key assumption of this work relies on the notion that individuals automatically calculate the value of presented stimuli, a hypothesis that has been supported in some recent findings [55•,56•,57]. It remains to be seen whether motivated individuals can deliberately manipulate these evaluations, a key question for economic applications.

Conflict of interest statement

None declared.

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