Chapter 22

The Brain is not "as-if" — Taking Stock of the Neuroscientific Approach on Decision Making

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1. Introduction

How do we make decisions? This question has long engaged researchers from various disciplines, including philosophy, psychology, economics, and cognitive neuroscience. Recently, a new discipline – neuroeconomics – emerged, devoted to addressing exactly this question by means of interdisciplinary endeavors. Broadly stated, neuroeconomics sets out "to promote interdisciplinary collaborations on the topics lying at the intersection of the brain and decision sciences in the hope of advancing both theory and research in decision making" (Society for Neuroeconomics, www.neuroeconomics.org), so that it can be used "for discriminating among standard economic models" (Maskin, 2008, p. 1788) and thus inform economic theory.

Neuroeconomics evolved as a field in the late 1990s, an offspring of behavioral economics and cognitive neuroscience. Behavioral economics is itself a relatively new field, just two decades old, and is commonly traced back to Herbert Simon's concept of bounded rationality (Simon, 1989). All three fields share the same goal of making theories of decision making more realistic by using insights from psychology or cognitive neuroscience. But what may be unrealistic about classical theories of decision making? It appears that there is little evidence that humans make decisions by calculating the expected utility (EU) or any of its variants outside the world of choices between gambles, if at all (e.g., Kahneman & Tversky, 2000; Lopes, 1981; Rubinstein, 1988; Russo & Dosher, 1983). Daniel Friedman and Shyam Sunder (2011) reviewed the literature on risky choice from 1950 up to 2010:

> Most theories of risky choice postulate that a decision maker maximizes the expectation of a Bernoulli (or utility or similar) function. We tour 60 years of empirical search and

> conclude that no such functions have yet been found that are useful for out-of-sample predictions. Nor do we find practical applications of Bernoulli functions in major risk-based industries such as finance, insurance and gambling. (p. 1)

The important methodological concept is "out-of-sample prediction." There is plenty of evidence that EU theory and its variants, such as prospect theory, can *fit* their parameters to data after the fact, but the real test is in *prediction*. "Out of sample" means that a utility function is fitted to a randomly chosen part of the data – say one half – and the fitted function is then tested on the other part (known as *cross-validation*). If the fitted utility function captures the actual process of decision making, then that function should predict the same person's or group's choices. Friedman and Sunder (2011) claim having found no evidence of this in the 60 years of research they reviewed, neither for individual utility functions nor for group utility functions, where groups are defined by demography, gender, and the like.

Neoclassical economists have, in fact, never proposed that people actually weight utilities with probabilities and carry out computations to maximize expected utility. On the contrary, they insist that their theory says nothing about processes either at the level of cognitive psychology and/or its neural implementation. Following Milton Friedman's (1953) "as-if" methodology of "positive economics," neoclassical economists, like the behaviorist B. F. Skinner, saw value only in predicting behavior, not in modeling cognitive processes. EU theory, prospect theory, equity aversion theory, and other utility theories are "as-if" models that are deliberately *not* meant to model the cognitive processes or give information on the neural implementation. The theoretical direction that much of cognitive neuroscience on decision making has taken, however, is to apply the as-if framework as a theory for how the brain works. For example, Glimcher and his colleagues suggested that "the neoclassical/revealed preference framework might prove a useful theoretical tool for neuroscience" (Glimcher et al., 2009, p. 7). Subsequently, the concepts of 'expected value' and 'expected utility' found their ways into neuroeconomics, and there is broad consensus that neuroeconomics is about studying "the computations that the brain carries out in order to make value-based decisions, as well as the neural implementation of those computations" (Rangel et al., 2008, p. 545).

In this chapter, we will provide a positive alternative to the main path pursued by the cognitive neuroscience of decision making. One of the authors (GG) has spent decades on opening the "black box" and investigating the cognitive processes of decision making in humans (Gigerenzer, 2008; Gigerenzer et al., 1999, 2011), including expert groups of doctors, judges, and managers (Gigerenzer & Gray, 2011). Consistent with D. Friedman and Sunder (2011), Gigerenzer and colleagues found little evidence that utility functions predict (as opposed to fit) laypersons' and experts' behavior. Moreover, none of the professional groups investigated uses EU maximization in practice, while there is evidence that they rely strongly on heuristics (Gigerenzer et al., 2011). Given these findings and the overall aim of unraveling human decision making processes, we argue that the neuroscience of decision making would benefit from the following principles so as to approach a psychologically valid account of human decision making (in the brain):

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1. *Study the neural correlates of process theories, not of as-if theories.*

As explained above, the aim of as-if models, such as EU theory and its modifications is to explain behavior on an aggregate level by explicitly ignoring the underlying cognitive processes. Examples are the explanation of cabdrivers' labor supply decisions (Crawford & Meng, 2010), farmers' decision behavior given new Common Agricultural Policy (Serrao & Coelho, 2004), or individuals' risky choice behavior (Kahneman & Tversky, 1979). Cognitive neuroscience, however, is explicitly dedicated to the process level, i.e., cognitive neuroscientists want to understand "*how* [emphasis added] the brain enables mind" (Gazzaniga, 2000, p. xii). That is, the object of interest is "the cognitive rules that people follow and the knowledge representations that those rules operate on" (Gazzaniga, 2000, p. 6). Accordingly, the two disciplines work at different levels of description, paying – by definition – no or only little attention to how descriptions at one specific level are related to descriptions at other levels (e.g., Craver, 2007; Marr, 1982). Thus, testing for the neural correlates of EU theory or its variants appears to us as if researchers would interpret an as-if model as a cognitive process model. One solution to this inconsistency would be to test for the neural correlates of process models of decision making, such as heuristics and their adaptive use (Gigerenzer et al., 2011; Payne et al., 1992, 1993; Volz et al. 2006, 2010). For instance, research on investigating how the brain encodes magnitude and probability (e.g., Tobler et al., 2005; Preuschoff et al., 2006, 2008) or how risk is coded (Christopoulos et al., 2009) does not need the EU framework of weighting and integration (of all utilities and probabilities). Magnitude and probability are also components of heuristic models, such as the priority heuristic (Brandstätter et al. 2006; see below). Researchers testing for the neural correlates of an as-if model – such as EU and its variants – however, need to explain why they reinterpret these models in a way they were explicitly not meant to be interpreted.

2. *Study decision making in uncertain ("large") worlds, not only certain ("small") worlds.*

The large majority of neuroscientific studies on decision making examines behavior predominantly in situations where everything is known for certain, including all alternatives, consequences, and their probabilities (a so-called small world). A prototypical example is the gambling paradigm. Variants are probabilistic learning-or probabilistic tracking paradigms, in which events are exclusively governed by a specific probability function and individuals are encouraged to estimate the probability of reward. Tasks of the latter sort might be more or less difficult (e.g., depending on whether encountering a volatile or a stable environment, cp. Beherns et al., 2007), but individuals know on which variable(s) to concentrate, i.e., they know about the structure of the task.

To study decision making in gambling and similar small worlds can be an interesting subject. Yet as a study of cognitive processes, it is unclear what this approach can tell us about decision making under uncertainty, that is, situations where not all alternatives, consequences, and probabilities are known for sure. Recent research indicates that neither the normative nor the descriptive results can be automatically generalized. First, what is rational in small worlds is *not* generally rational in uncertain worlds (Gigerenzer et al., 2011). On the contrary, models that are optimal in a small world are typically only second-best when uncertainty is introduced, as in out-of-sample prediction or out-of-population prediction (Czerlinski et al., 1999; Gigerenzer & Brighton, 2009). One reason is that optimization models tend to overfit. Second, small worlds and large worlds may require entirely different skills and strategies. For example, whereas it might suffice to calculate the expected value in a lottery, this skill will not be sufficient for deciding whether or not to be vaccinated against swine flu, which share to buy, or whom to marry. Decision making under risk (small worlds) and under uncertainty (large worlds) do require different skills: statistical thinking and heuristic thinking. It is not possible to extrapolate from small to large worlds except for the rare case in which the former approximates the latter. Savage, known as the father of Bayesian decision theory, has drawn a clear line between the study of small and large worlds:

> Jones is faced with the decision whether to buy a certain sedan for a thousand dollars, a certain convertible also for a thousand dollars, or to buy neither and continue carless. The simplest analysis, and the one generally assumed, is that Jones is deciding between three definite and sure enjoyments, that of the sedan, the convertible, or the thousand dollars. Chance and uncertainty are considered to have nothing to do with the situation. This simple analysis may well be appropriate in some contexts; however, it is not difficult to recognize that Jones must in fact take account of many uncertain future possibilities in actually making his choice. The relative fragility of the convertible will be compensated only if Jones's hope to arrange a long vacation in a warm and scenic part of the country actually materializes; Jones would not buy a car at all if he thought it is likely that he would immediately be faced by a financial emergency arising out of the sickness of himself or of some member of his family; he would be glad to put the money on a car, or almost any durable goods, if he feared extensive inflation." (Savage, 1954, p. 83)

Note that studying decision making under uncertainty (as opposed to risk) does not require bringing the complexity of the world into the scanner. It only requires studying tasks where not all alternatives, consequences, and probabilities are known for sure. Well-known examples of large world paradigms are the city task by Goldstein and Gigerenzer (2002), in which individuals are presented with pairs of cities (e.g., Portland – Virginia Beach) and have to infer which city in each pair had the larger population, the fever task by Persson & Rieskamp (2009), and Bröder et al.'s (2010) tasks in which individuals have to judge which of two patients (each with a specific combination of symptoms) had reached the more advanced and dangerous stage.

3. *Implement predictive and competitive tests as methodological standards.*

The practice of using good fits to support theories has been very popular, in psychology as well as in behavioral economics in the past. However, a good fit by itself is not an adequate test of a theory (Roberts & Pashler, 2000; Roberts & Sternberg, 1993; Wexler, 1978). Fitting means that the data is already known, and dependent on the number and kind of adjustable parameters, one can always achieve a good fit. Accordingly, the practice is now changing and researchers now determine how the theory constrains

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possible outcomes (i.e., how well it predicts), how actual outcomes agree with those constraints, and whether plausible alternative outcomes would have been inconsistent with the theory (Ahn et al., 2008; Roberts & Pashler, 2000; Bröder et al., 2010; Persson & Rieskamp, 2009). Besides fitting, a second limitation of many tests is that only one theory is being tested, and one does not know whether other theories would predict behavior better. Examples for competitive tests are found in Brandstätter et al., (2006) on models predicting choice between lotteries (small worlds), and in Dhami (2003) on British magistrates' bail decisions (uncertain worlds). Following up on this progression, we would like to push forward the implementation of predictive and competitive tests also in the cognitive neuroscience of decision making, which only now started to be pursued (e.g., Christopoulos et al., 2009; Venkatraman et al., 2009). Obviously, we specifically would like to suggest incorporating heuristic models in competitive testing on the neural level since this hasn't been pursued intensively yet. Exceptions are from our own research: In an fMRI study on the neural correlates of the Recognition Heuristic (RH)[1], we predicted the neuronal activation patterns that different theories for RH-based decisional processes made. Results revealed that processes underlying RH-based decisions go beyond simply choosing the recognized alternative and are rather distinguished by judgments about the ecological rationality of the RH (Volz et al., 2006).

The three issues are linked. We begin our discussion of them by introducing the basic concepts of modern decision theory and methodology.

2. As-If models and process models

It is often worthwhile to ask where ideas come from. That helps to understand why we ask the questions we ask. Expected value theory has its origin in the social gambling behavior of aristocrats. Its year of birth is commonly dated 1654, when the Chevalier de Méré asked the mathematicians Pierre Fermat and Blaise Pascal for advice in gambling. Their exchange of letters is seen as the beginning of probability and decision theory (for the psychological interpretation of the classical theory, and decline, see Daston, 1988; Gigerenzer et al., 1989). The resulting theory of rational choice is known today as expected value (EV) theory:

$$\mathrm{EV}(x) = \sum p_i x_i \tag{1}$$

where p_i is the probability and x_i the (monetary) value of each outcome (i=1, …, n) of a given alternative x. For example, being offered the choice between two alternatives, Gamble A: 490.000€ with p=1.0 and Gamble B: 1 million with p=.5 and 0€ with p=.5, which would you choose? According to EV theory, you should choose the risky Gamble B because it maximizes EV. However, the choices of reasonable people did not always conform to theory. This

1 The RH can be stated as follows: "If one of two objects is recognized and the other is not, then infer that the recognized object has the higher value with respect to the criterion." (Goldstein &Gigerenzer, 2002, p. 76).

discrepancy received the greatest attention in the St. Petersburg problem, which led Daniel Bernoulli (1738/1954) to modify EV theory into what is now called expected utility (EU) theory:

$$\mathrm{EU}(x) = \sum p_i u_i \tag{2}$$

As one can see, the basic idea is the same: Instead of choosing the alternative that maximizes EV, one now chooses the alternative that maximizes EU. Bernoulli assumed that u=log(x), modeling diminishing returns, but other functions have been proposed, including nonmonotonic functions (e.g., Friedman & Savage, 1948). In the second half of the 20th century, systematic deviations from EU theory were shown in experimental studies, including the Allais paradox and the fourfold pattern (Kahneman & Tversky, 2000; Lopes, 1994). Simon (1989) and Selten (2001) proposed a radical break from EU theory, based on empirical psychological principles, such as the study of adaptive heuristics (Gigerenzer et al., 1999; Leland, 1994; Payne, Bettman, & Johnson, 1993; Tversky, 1972). However, most of the economic community retained the EU framework but modified it by adding more adjustable parameters, as in prospect theory (Kahneman & Tversky, 1979):

$$V(x) = \sum_{i=0}^{n} \pi_i^{+} v(x_i) + \sum_{i=-m}^{0} \pi_i^{-} v(x) \tag{3}$$

where π are the decision weights for positive and negative domains (gains and losses). The added flexibility – five adjustable parameters – fitted the data better than EU theory, as long as the additional parameter values were suitably chosen. Given that the form of the relation between u and x is left unspecified, one has to estimate it for each person or group. Yet, as mentioned above, the fitted utility functions of EU and its modifications have not been shown to be useful in out-of-sample prediction of behavior (Friedman & Sunder, 2011). The problem that Bernoulli functions lack predictive power is rarely mentioned in the neuroscience literature.

Prospect theory and similar attempts to make models of decision making more realistic led to "the paradoxical result that the models became even less psychologically plausible" (Gigerenzer & Selten, 2001, p. 5). For example, try to compute the subjective values of risky prospects following prospect theory:

> An individual chooses among two or more lotteries according to the following procedure. First, transform the probabilities of all outcomes associated with a particular lottery using a nonlinear probability-transformation function. Then transform the outcomes associated with that lottery (i.e., all elements of its support). Third, multiply the transformed probabilities and corresponding transformed lottery outcomes, and sum these products to arrive at the subjective value associated with this particular lottery. Repeat these steps for all remaining lotteries in the choice set. Finally, choose the lottery with the largest

> subjective value, computed according to the method above. (Berg & Gigerenzer, 2010, pp. 4-5)

Yet, as explained above, prospect theory should not be mistaken as a cognitive process model. On the contrary, economists since Samuelson (1937) and Friedman (1953) have thought of EU and its variants as *as-if-models*, not as theories that describe the cognitive or neural processes, and neoclassical economists treat the mind as a black box. Economic theory is about the prediction of behavior, not of process. This is the main reason why many economists see little value in neuroeconomics (for economic research) (e.g., Gul & Pesendorfer, 2008; Harrison, 2008; Marchionni & Vromen, 2010; Rubinstein, 2008).

Hitherto, most of the neuroscience of decision making set out to investigate the neural correlates of as-if models, assuming that the mind engages in some form of utility calculations. A great number of neuroeconomic studies aimed at identifying "the brain activations coding the key decision parameters of expected value (magnitude and probability)." (Tobler et al., 2007, p. 1621). Fox and Poldrack (2009, p. 165) claim that there "has been substantial progress in understanding the neural correlates of prospect theory." Others present the assumptions of EU theory as true with regard to the cognitive processes weighting and integrating, but did neither proof whether individuals indeed engaged in these cognitive processes nor elaborated on the issue of as-if models vs. process models. "Decision makers integrate the various dimensions of an option into a single measure of its idiosyncratic subjective value and then choose the option that is most valuable. Comparisons between different kinds of options rely on this abstract measure of subjective value, a kind of "common currency" for choice" (Kable & Glimcher, 2009, p. 734).

The assumption that choice is always based on a weighted integration of all relevant aspects is the most widely held belief across disciplines when it comes to decision making processes; irrespective of whether decisions entail choosing between risky prospects, such as in gambling situations, or between uncertain options, such as a suitable capital investment, a proper university degree, or a life partner: "When deciding between different options, individuals are guided by the expected (mean) value of the different outcomes and by the associated degrees of uncertainty." (Tobler et al., 2007, p. 1621).

These claims are somewhat astounding, at least to us. The experimental literature indicates that full integration (compensation) of the various attributes is the exception rather than the rule (e.g., Gigerenzer & Gaissmaier, 2011; Hauser, 2011; Marewski et al., 2010). Often, humans rely on heuristics that are noncompensatory, such as one good reason or lexicographic decisions. A classic review of 45 studies in which the process of decision making was analyzed by means of eye movement, mouse lab, and other process tracking studies concluded:

> The results firmly demonstrate that non-compensatory strategies were the dominant mode used by decision makers. Compensatory strategies were typically used only when the number of alternatives and dimensions were small or after a number of alternatives have been eliminated from consideration. (Ford et al., 1989, p. 75)

Influential neuroeconomic papers, including those cited above, yet, seem to focus on the EU framework and hence seem to accept its basic assumptions as a realistic description of cognitive and neural processes. These assumptions about the nature of decision making thus include (Katsikopoulos & Gigerenzer, 2008):

1. *Independent evaluations:* Every option has a value that is measured by a single number (options are not evaluated relative to other options).
2. *Exhaustive search:* The value of an option is calculated by using all available information (for gambles, the probabilities and values for all possible outcomes).
3. *Trade-offs:* To calculate an option's value, low values on one attribute (e.g., a value) can be compensated by high values on another attribute (e.g., a probability).
4. *Optimization.* The final choice is based on the maximization of utility or some other function of value.

These four assumptions are maintained through almost all modifications of EU theory; what is modified in reaction to inconsistent data are the functions of the probabilities and values, as illustrated in Equations 2 and 3. Most important, the optimization assumption requires studying a small world in which all alternatives, consequences, and probabilities are known, as in a lottery. We will turn to the consequences of this assumption below.

What would a process model look like? A process model would not take the four assumptions as axiomatic, but consider the empirical evidence. In brief, evidence shows that the first three assumptions sometimes hold, typically in small worlds, but are most of the time not descriptively correct (e.g., Bröder & Gaissmaier, 2007; Hauser, 2011). Specifically, there is little evidence that individuals use the same strategy for each decision; instead it implements an "adaptive toolbox" with multiple strategies, called heuristics (Bröder et al., 2010; Persson & Rieskamp, 2009; Gigerenzer & Selten 2001; Honda et al., 2011; Payne et al., 1993). One interesting result is that whereas modifications of EU such as prospect theory grow increasingly complex in order to represent deviating behavior in the EU framework, simple heuristics that are based on evidence on cognitive processes can dispense with this added complexity. One illustration of a process model is the priority heuristic, which applies to lotteries (Brandstätter et al., 2006). Like many heuristics, it has three building blocks: a search rule, a stopping rule, and a decision rule.[2] The priority heuristic consists of the following steps:

Search rule: Go through reasons in the following order: minimum gain, probability of minimum gain, maximum gain.

Stopping rule: Stop examination if the minimum gains differ by 1/10 (or more) of the maximum gain; otherwise, stop examination if probabilities differ by 1/10 (or more) of the probability scale.

Decision rule: Choose the gamble with the more attractive gain (probability).

The term "attractive" refers to the gamble with the higher (minimum or maximum) gain and the lower probability of the minimum gain. The priority heuristic models difficult choices (same or similar expected values of the alternatives) and nontrivial choices (no alternatives

2 Note that EU theory has no search and stopping rules, because it assumes full information or exhaustive search.

dominates the other, weakly or strongly). The search, stopping, and decision rules were derived from psychological studies (Brandstätter et al., 2006, 2008).

Consider one of the problems, known as the Allais paradox, which shows an inconsistency between the actual observed choices and the predictions of EU theory, or more specifically the transgression of the common consequence effect (Allais 1953, p. 527):

A:	100	million	for *sure*
B:	500	million	$p=.10$
	100	million	$p=.89$
	0		$p=.01$
C:	100	million	$p=.11$
	0		$p=.89$
D:	500	million	$p=.10$
	0		$p=.90$

Most people prefer *A* over *B*, but *D* over *C*, violating EU theory (because *C* and *D* are obtained from *A* and *B* by eliminating a.89 probability to win 100 million from both gambles). EU does not predict whether *A* or *B* will be chosen; it simply makes predictions of the type "if *A* is chosen over *B*, then it follows that *C* is chosen over *D*." The priority heuristic, in contrast, makes stronger predictions: It predicts whether *A* or *B* will be chosen, and whether *C* or *D* will be chosen. Consider the choice between *A* and *B*. The maximum payoff is 500 million, and therefore the aspiration level is 50 million; 100 million and 0 represent the minimum gains of the choice problem. Because the difference (100 million) exceeds the aspiration level of 50 million, the minimum gain of 100 million is considered good enough and people are predicted to select gamble *A*. That is, the heuristic predicts the majority choice correctly.

In the second choice problem, the minimum gains (0 and 0) do not differ. Hence, the probabilities of the minimum gains are attended to, *p*=.89 and.90, a difference that does not meet the aspiration level. Thus, the higher maximum gain (500 million versus 100 million) decides the choice, and the prediction is that people will select gamble *D*. Again, this prediction is consistent with the choice of the majority. Together, the pair of predictions amount to the Allais paradox.

This simple three-step process generates not only the Allais paradox, but several other so-called anomalies as well. It simultaneously implies common consequence effects, common ratio effects, reflection effects, and the fourfold pattern of risk attitude (Katsikopoulos & Gigerenzer, 2008). Note that the priority heuristic logically *implies* these behaviors, whereas prospect theory is only *consistent* with these.

The priority heuristic is an example of a process model that assumes dependent rather than independent evaluation: First, the two alternatives are compared, one by one, on the attributes, rather than each alternative having a utility independent of the other. Second, it assumes limited rather than exhaustive search, that is, it does not always use all of the information but employs a stopping rule. Third, it makes no trade-offs between the attributes: For instance, the first attribute alone can determine the decision. Finally, it is not based on the computation of a maximum or minimum of a function including weighting and summing, but is a model of bounded rationality in the sense of Simon.

In sum, EU theory and its modifications have been proposed as as-if models in neoclassical economics precisely because there is little evidence that they describe the psychological or neuronal processes underlying a decision. Behavioral economics largely retained the as-if framework, adding realism in the form of one or a few adjustable parameters and continuing to produce as-if models (Berg & Gigerenzer, 2010). Given this fact and the case that cognitive neuroscience investigations are by definition foremost interested in process models, we wonder why most of neuroeconomic research attempted to locate the computations involved in as-if theories in the brain and did not turn to distinct process models of decision making. Thus, an alternative is to study the neural correspondents of heuristic processes, such as search rules, stopping rules, and decision rules (e.g., Volz et al., 2006, 2010).

3. The brain is adapted to the uncertainty of large worlds, not to the certainty of lotteries and small worlds

EU and its modifications all involve optimization. Optimization means finding the maximum or minimum of a function and proving that it is the best choice. Optimization requires a world in which all alternatives, consequences, and probability distributions are known for certain (otherwise one cannot know what the optimal alternative is). L. J. Savage (1954) distinguished between small worlds in which these conditions are met and where Bayesian theory is optimal, and large worlds in which these conditions are not met and where it would be "ridiculous" to use Bayesian decision theory (Binmore, 2008). The prototype for a small-world problem is the lottery. Many of the standard neuroscientific tasks on choice and decision making have been modeled after the lottery: two-armed bandit tasks, intertemporal choice tasks, and the ultimatum game, among others. For example, in the financial decision-making task by De Martino and colleagues (2006), participants had the choice between a sure option, i.e., how much money can be won on a specific trial (v=£20 with p=1.0) and a gamble option, i.e., the exact specification of the probabilities of winning or losing a specific amount of money (v=£50 with p=.37 and v=£0 with p=.63). Likewise, outcomes are certain in intertemporal choice paradigms, where, for instance, participants have to choose between smaller monetary rewards delivered immediately (€13.83 today) and larger monetary rewards delivered only later (€17.29 in 4 weeks) (e.g., Albrecht et al., 2011; McClure et al., 2004).

Without any disparagement intended, we note that these conditions rarely apply to real-world decisions. In the real world, part of the relevant information is missing or has to be estimated from small samples and the future is naturally unpredictable, so that optimization is out of reach. Such decisions include which capital investment to favor, which used car to buy, or whether to take a specific cancer check-up. Moreover, even if all alternatives, consequences, and probabilities are known, computing the best alternative in such situations can be computationally intractable. For example, computing Bayes' rule is NP-hard, that is, it becomes computationally intractable for brain and computers alike when large numbers of attributes

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are involved. Even in the simplest case with binary predictors only and a binary criterion, the number of leaves (exits) of the full decision tree increases exponentially (2^n) with the number n of predictors. In contrast, in a fast-and-frugal tree, which is a heuristic model of Bayesian-type decision making, the number of leaves increases with n+1 only (Martignon et al., 2011).

3.1. Cognitive processes in large worlds differ from those in small worlds

The crucial question is, what can we learn about the brain if we focus experimental tasks on small worlds? Can we generalize the findings from small-world studies to uncertain worlds? Consider first the sub-question: Can we generalize the norms? To begin with, note that the very reason to construct small worlds is that EU theory or some other optimization model can be used to determine the best alternative. But the best strategy in a small world is not necessarily the best one in a large world. By way of illustration, two examples may suffice. Consider financial investment once again. A normative theory of how to allocate a sum of money to *N* assets is Markowitz's Nobel prize-winning mean-variance model. Like all optimizing theories, it assumes perfect knowledge about the relevant parameters. Is the theory optimal in the real world of financial investment, where parameter values are not known for certain but need to be estimated? The answer is no. De Miguel and colleagues (2009) showed that the simple 1/*N* heuristic (allocate your money equally to *N* assets) performs better in out-of-sample prediction. Note that the heuristic achieves better performance because it ignores part of the information, which makes it robust, while the mean-variance portfolio tries to integrate all information to estimate the weights and suffers from overfitting.

Second, consider sequential decision making where cues need to be ordered in a way that improves inductive inferences. The optimal ordering can be determined easily in a small world, and it leads to more accurate inferences than when cues are ordered simply, as with the take-the-best heuristic. Yet, in out-of-sample prediction, the optimal ordering is no longer best, and the simple ordering leads to more accurate inferences (Gigerenzer & Brighton, 2009; Martignon & Hoffrage, 1999). These results illustrate *less-is-more effects*, that is, situations where less computation and information enables more accurate inferences. They also explain why a certain degree of memory and capacity limitations can be beneficial (e.g., Goldstein & Gigerenzer, 2002; Hertwig & Todd, 2003). The study of *ecological rationality* answers the question of the worlds in which a given heuristic is successful, relative to other strategies. For instance, to allocate one's money to *N*=50 assets, an estimated 500 years of stock data would be needed for the mean-variance portfolio to finally exceed the performance of the 1/*N* heuristic (DeMiguel et al., 2009).

In sum, good decision making in large worlds requires different cognitive processes than those studied in small worlds. Studying a world of certainty may very likely miss the cognitive processes in the brain that deal with uncertainty (such as limited search and aspiration levels), making extrapolation simply not feasible. Furthermore, one cannot extend claims about a person's cognitive processes based on a rational or irrational behavior in a small world to corresponding claims for the same person in a large world.

3.2. Bounded rationality is the study of cognition in "Large worlds"

In behavioral economics, the term "bounded rationality" is correctly attributed to H. A. Simon but incorrectly identified with a program that is not his: the study of deviations from optimality. For instance, Daniel Kahneman (2003, p. 1449) noted: "Our research attempted to obtain a map of bounded rationality, by exploring the systematic biases that separate the beliefs that people have and the choices they make from the optimal beliefs and choices assumed in rational-agent models." In this research, it is assumed that the conditions for rational models (i.e., for a small world) hold and can thus define optimal reasoning. Simon (1989), however, asked a fundamentally different question, leading to a different research program:

> How do human beings reason when the conditions for rationality postulated by the model of neoclassical economics are not met? (p. 377)

The study of behavior in lotteries – and other small worlds where the conditions of rationality are met – does not address Simon's question. In large worlds, people cannot optimize, but need to satisfice by relying on heuristics from the brain's adaptive toolbox. The term "satisficing", originally introduced by Simon, is the Northumbrian term for "satisfying" and is used to refer to decision strategies that ignore part of the available information and involve little computation. For example, when having to decide quickly whether an incoming patient should be treated as low-risk or high-risk in an emergency room, medical decisions implement fast and frugal heuristics (cp. Gigerenzer et al., 1999). We believe that as long as research continues to focus on small worlds, we will learn little about the brain's decision processes that people use *outside the laboratory*, i.e., in uncertain decision situations, which structurally differ from small world problems.

Why are lotteries studied so extensively in decision research and neuroeconomics and used to define rational choice? This appears particularly surprising given that we do not come across gambling situations very frequently in the real world, nor that most of our daily decision situations structurally resemble gambling situations. There are probably three reasons for this tradition. The first is the historical origin of aristocrats asking mathematicians for advice on gambling problems – not on whom to marry, what job offer to accept, or how to invest money wisely. The second reason is the fondness for optimization models. And the third is the misinterpretation of Simon's concept of bounded rationality as constrained optimization, or the deviation of human judgment from optimization.

In sum, much of cognitive neuroscience studies decision making in small worlds, where optimization is defined. This focus imposes limits on the understanding of brain processes, both normatively and descriptively. Normative behavior in a small world is not necessarily so in large worlds, where robustness counts. Furthermore, cognitive processes underlying bounded rationality, such as heuristic search, stopping rules, and aspiration levels, have little chance of being "detected" when one is looking for the neural correlates of EU theory and other as-if theories.

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4. Methodology

4.1. Prediction versus fitting

In their methodological critique of behavioral economics, Binmore and Shaked (2010) recall the importance of distinguishing between data fitting and prediction:

> The scientific gold standard is prediction. It is perfectly acceptable to propose a theory that fits existing experimental data and then to use the data to calibrate the parameters of the model. But, before using the theory in applied work, the vital next step is to state the proposed domain of application of the theory and to make specific predictions that can be tested with the data that was used neither in formulating the theory nor in calibrating its parameters. (p. 89)

Whereas the dependent variable in behavioral decision research is the actual choice behavior of individuals, groups, or the entire economy, the primary dependent variable in almost all neuroeconomic studies to date is the BOLD signal change. Accordingly, the gold standard in neuroscience is the prediction of the BOLD response as a function of the manipulation of the independent variable(s). Neuroeconomic studies thus aim at predicting the BOLD signal changes as a function of choice behavior, or, in the words of Glimcher and colleagues (2009, p. 7): “Neuroscientists […] were interested in describing the algorithmic mechanisms of choice. Their goal was to describe the neurobiological hardware that supported choice behavior in situations ranging from perceptual decision making to the expression of more complicated preferences.” Yet the authors also noted that “what they [the neuroscientists] lacked was an overarching theoretical framework for placing their neural measurements into context.” This lacuna was filled by Glimcher and colleagues' (2009) suggestion “that the neoclassical/revealed preference framework might prove a useful theoretical tool for neuroscience. What followed was the rapid introduction to the neuroscientific literature of such concepts as expected value and expected utility” (p. 7).

This statement reveals three issues that we propose to characterize the state of the art in current neuroeconomic research:

1. Cognitive neuroscientific and neuroeconomic research on decision making primarily pursues the neoclassical as-if approach while so far neglecting process theories, such as the program on fast-and-frugal heuristics (cp. Gigerenzer, Hertwig, & Pachur, 2011; for exceptions, see Volz et al., 2006, 2010).

2. The predominant focus on concepts such as expected value and expected utility has led to the generally accepted assumption in the cognitive neuroscience literature on decision making that the choice process comprises a first evaluation stage in which values for each option are determined and a subsequent decision stage in which the individual chooses on the basis of this common currency. Accordingly, these two stages have been investigated separately, and a considerable number of studies have focused on the neurobiological implementation of the anticipation/valuation phase, which is – by definition – characterized by a lack of choice behavior. As noted above, there is no compelling

empirical evidence supporting the assumption that decision makers go through the stages of the expected value or utility model (e.g., Ford et al., 1989; Friedman & Sunder, 2011; Venkatraman et al., 2009). Even in gambling situation, individuals seem to process information in a way that is incompatible with the EU framework, as revealed by imaging studies (Venkatraman et al., 2009), verbal protocol studies (Cokely & Kelley, 2009), eye tracking studies (Russo & Dosher, 1983), and information board studies (Mann & Ball, 1994; Payne & Braunstein, 1978).

3. The presentation of data on the neurobiology of value-based decision making, which are considered to "yield new insights into behavior" (Kable & Glimcher, 2009, p. 734), may make researchers forget that neuroimaging does *not* allow "to look into the head" objectively or "watch the brain while deciding". Rather, by setting up an experiment, researchers are driven by their theoretical assumptions, which subsequently lead to very specific experimental manipulations, such as manipulating the probability and the value of choice options, as well as to very specific analyses, such as conducting an analysis "to identify candidate regions whose activity correlated with a linear model of EV." (Knutson et al., 2005; p. 4807). Thus, fMRI data themselves do not tell us what is going on in the brain. The data are always interpreted in light of a theory; more important, the very choice of a theory determines a study's problems and experimental set-up. For instance, optimization theory, such as EU and Bayes, confines studies to small worlds, where *the* best outcome is computationally tractable.

Returning to the issue of the degree to which neuroeconomic studies use prediction, we would like to recapitulate that the scientific method is hypothesis-driven. In other words, (neuroeconomic) researchers *first* hypothesize about the alleged brain areas being crucially involved in the respective cognitive process(es) and *then* conduct significance testing. Hypothesis-driven research needs to be distinguished from so-called "see-and-tell" studies or "fishing expeditions." The latter are appropriate for finding hypotheses, but should not be presented as testing hypotheses by performing significant tests after the fact. The practice of (mis)presenting a hypothesis-finding study as a hypothesis-testing study is possibly due to disregard for the value of hypotheses finding, high degrees of freedom in data collection and post hoc analysis, and the practice of null-hypothesis significance testing (NHST) (Loftus, 1996; Simmons et al., 2011; Vul et al., 2009). This is not to say that we take issue with research that describes the data of an experiment, which may lead to specific testable predications; we solely disapprove of presenting significant results after the fact, that is, selling ad hoc interpretations as genuine experimental hypotheses testing.

Many neuroeconomic studies use prediction. That is, as a function of the experimental design, more or less elaborated anatomical hypotheses are made. For example, in the realm of value-based decision making, it has been predicted and shown that the ventral striatum encodes the subjective value of both primary records (e.g., pleasant sweet taste [O'Doherty et al., 2002], naturalistic food aromas [Bragulat et al., 2010], or erotic stimuli [Sescousse et al., 2010]) and secondary rewards (e.g., money [Delgado et al., 2000; Elliott et al., 2000; Knutson et al., 2000]); that the ventral striatum reflects the anticipation and expectation of (monetary) rewards (Breiter et al., 2001; Knutson et al., 2000, 2003, 2005; Preuschoff et al., 2006;); and that the ventral striatum is directly related to an individual's actual behavioral preferences (Kable & Glimcher, 2007; O'Doherty et al., 2006;). A similar story seems to hold for the medial prefrontal cortex (mPFC) (e.g., Elliott et al., 2003; Lebreton et al., 2009; Plassmann et al., 2007; Tom et al., 2007; for a review see Rushworth et al., 2011). That is, the mPFC seems to reflect the "some aspect of both expected reward value prior to the making of a choice and the received reward value after a choice is made" (Rushworth et al., 2011, p. 1056). Contemporary research suggests that the mPFC valuation signal is an automatic one reflecting the value of an option even in the absence of any choice (Lebreton et al., 2009; Smith et al., 2010). Further endeavors to differentiate the roles of the mPFC and the ventral striatum suggested that the latter specifically represents anticipated gain magnitude, whereas the mPFC also represents anticipated gain probability; it was also suggested that the mPFC integrates the two components of expected value (Knutson et al., 2005; Knutson & Wimmer, 2007; but see also Behrens et al., 2007; Rushworth & Behrens, 2008, for the suggestion that anterior cingulate cortex activity encodes the integrated value of actions).

In the realm of intertemporal choice, it has been predicted and shown that decisions involving immediately available rewards draw specifically on limbic structures, whereas intertemporal choices per se, irrespective of delay, draw on the lateral prefrontal cortex and associated structures (Albrecht et al., 2010; McClure et al., 2004; Mitchell et al., 2011). Moreover, by taking into account the actual choice behavior of subjects, it has been predicted and shown that activity in the ventral striatum, the mPFC, and within the posterior cingulate cortex "tracks the revealed subjective value of delayed monetary rewards" (Kable & Glimcher, 2007, p. 1625). In the realm of social decision making, activation within neural structures that are involved in emotional processing, such as the insula and amygdala, have been predicted and shown to be activated for a number of so-called decision anomalies such as rejecting unfair offers in the UG (Sanfey et al., 2003; Tabibnia et al., 2008), reciprocating trust (van den Bos et al., 2009), displaying inequity aversion (Haruno & Frith, 2010), or third-party punishment decisions (Buckholtz et al., 2008); for an overview, see Rilling & Sanfey, 2011). Amygdala or insula activation has generally been considered to provide important affective biases to social decisions.

All these predictions were made in small world settings, where all alternatives, consequences, and probability distributions were known or could be learned from experience. That is, participants had to value specific items such as food, money, or specific abstract symbols representing money, or had to choose between (two) risky outcomes. As outlined before, these results are very interesting by itself and can help in determining the cognitive processes involved in different decision making tasks. For example, individuals using the priority heuristic (PH) when making decisions between risky gambles, by definition, first go through the reasons in the order of minimum gain, probability of minimum gain, maximum gain and they stop their examination if the minimum gain differs by 1/10 (or more) of the maximum gain; otherwise they stop the examination if probabilities differ by 1/10 (or more) of the probability scale. Given the formal description of the PH, individuals applying the PH simply compare the numbers of the two gambles and thus the corresponding anatomical hypothesis would predict activation within a parietal network, which has been shown to support number comparison processes (Deheaene & Cohen, 1995; Pinel et al., 2001). Yet, if activation within striatal, dorsal anterior cingulate cortex, or inferior frontal cortex would elicit, i.e., within the network suggested to reflect processes involved in EU calculations, this finding would raise issues.

4.2. Competitive tests of models versus testing only one

Given the abundance of evidence on the neurobiology of choice behavior, "for a neuroeconomist, then, these studies constitute overwhelming evidence that a value system exists and can be functionally localized" (Glimcher, 2009, p. 514). This may certainly apply to small world settings. Yet, achieving a good fit of the expected value model/neoclassical framework to the neuroscientific observations does not necessarily mean that a good model or *the* best model is found. This is because "all models are wrong, but some of them predict better than others and may lead to novel questions" (Gigerenzer & Gaissmaier, 2011). Thus, although EV models and their variants may capture the algorithmic mechanisms of choice behavior for small-world problems, a convincing argument would require tests of several models to determine how well the model of choice performs against competing ones. This procedure differs from the widespread practice of null hypothesis testing. Since neuroeconomics seeks an algorithmic description of the mechanisms for choice behavior and the cognitive strategies underlying economic and everyday decisions, implementing comparative tests of formal models seems indispensable. Only by pursuing this strategy, we presume, can one accomplish the ambitious aim of describing the mechanisms of how decisions are made (in the brain).

To our knowledge, hitherto there are only a handful of imaging studies that use competitive testing on the neural level, for example in risky decision making (Basten et al., 2010; Christopolous et al., 2010; Hsu et al., 2009; Venkatraman et al., 2009) and we are not aware of imaging studies that tested whether competing models such as heuristic models (e.g., priority heuristic for risky gambles) fit to the neural data. We would be eager to learn whether the activation in a specific area may be equally or better explained by a competing (heuristic) model of choice.

One reason for this may be that in the implemented small-world problems, the very experimental set-up primes one specific strategy, namely EV calculations. Experimenters may have thereby induced the decision strategy in which they were interested. For example, in gambling paradigms the only information that is presented concerns probabilities and incentives (e.g., Behrens et al., 2007; Cooper & Knutson, 2008; De Martino et al., 2006; Elliott et al., 2000; Hsu et al., 2009; Knutson et al., 2005; Shiv et al., 2005; Preuschoff et al., 2006, 2008; Tom et al., 2007; Yacubian et al., 2006). Nevertheless, different decision strategies are also conceivable in gambling paradigms, such as probability matching, the priority heuristic, guessing, win-stay/lose-shift and others whose correlates could be investigated and compared (for probability matching in monkeys, see Morris et al., 2006; Niv et al., 2006). Indeed, Venkatraman and colleagues (2009) when investigating risky choice behavior on the neural level, found neural predictors of strategic variability in decision making: "Choices that maximized gains or minimized losses were predicted by fMRI activation in ventromedial prefrontal cortex or anterior insula, respectively. However, choices that followed a simplifying strategy (i.e., attending to overall probability of winning) were associated with activation in parietal and

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lateral prefrontal cortices." (p. 593). Most interestingly, activation within the mPFC predicted individual variability in strategic preferences through differential functional connectivity with parietal and insular cortex. In our view, studies like Venkatraman's et al. are very promising and should be extended to large world decision situations.

With these exceptions, the focus hitherto has been on the investigation of the anticipation/ expectation phase, in which participants are presented with a specific gamble, bet, or other well-defined option and are encouraged to choose advantageously. For example, in the probabilistic monetary incentive delay task by Knutson and colleagues, participants in the anticipation phase were presented with an icon indicating exactly the incentive that could be obtained on that specific trial and its probability. After having seen the trial specification, participants awaited the feedback, which was probabilistically determined, sometimes even independent of participants' choice. The fMRI analyses in studies using such small world settings are generally stimulus-dependent, that is, regressors are generated on the basis of measures built into the task, such as magnitude of gain/loss, probability of gain/loss, valence or salience of events, trial-specific EVs, or the like. Accordingly, analyses reveal activation in areas responsible for processing specific task characteristics.

Recently, further progress has been made in showing – for risky decisions– that in combining information from the three areas that are particularly responsive to changes in magnitude (striatum), objective risk coding (doral anterior cingulate cortex (dACC)), and risk aversion (inferior frontal gyrus (IFG)), "these BOLD responses were informative enough to allow an ideal observer to detect the overt choice: a risky choice was more probably when striatal and cingulate activity was higher, whereas increased BOLD signals from IFG correlated with increased probability of a safe choice" (Christopoulos et al., 2009, p. 12581). In other words, the BOLD responses from these areas combined essentially decoded the behavioral choice.

Such findings are very interesting by itself and especially give information on how the brain (in small world settings) encodes and processes specific task characteristics and combines them to produce overt choice behavior; yet, it remains an open and interesting issue whether these processes will manifest themselves in large world decision situations alike. In other words, the description of the neurobiology of value-based decisions in the small world does not necessarily imply these processes and activations in large-world decisions, yet this remains to be seen. To clarify this problem, we recommend imaging studies on large-world decisions that determine and compare the neural correlates of different decision strategies, including those modeled by the neoclassical approach and the heuristic approach.

Another recent development, which we think should be pursued and extended, is model-based fMRI, "which involves the application of computational models in the design and analysis of neuroimaging experiments" (O'Doherty et al., 2007, p. 35). The standard operating procedure is to "first fit the computational model to subjects' actual behavior to find specific values for the free parameters in the model […]. Once the best-fitting model parameters have been found, then the different model components can be regressed against the fMRI data […] to identify areas where the model-predicted time series show significant correlations with the actual changes in blood oxygenation level-dependent (BOLD) signal over time." (O'Doherty et al., 2007, p. 37). This model-based approach has been used to investigate questions of how the brain integrates cost and benefits during decision making (Basten et al., 2010), how it trades off between amount and delay during intertemporal decisions (Kable & Glimcher, 2007), how different experiences (volatility) are weighted in guiding future actions (Behrens et al., 2007), and whether the brain encodes a nonlinear probability function when evaluating risky choices as predicted by prospect theory (Hsu et al., 2009; Boorman & Sallet, 2009). Accordingly, in the various studies, the authors fitted several functions to the subjects' actual choices (e.g., various nonlinear probability-weighting functions or discount functions) and used the best fitting ones for the fMRI analyses. Results were interpreted to show that "the brain, thus, weighs costs against benefits by combining neural benefit and cost signals into a single, difference-based neural representation of net value" (Basten et al., 2010, p. 21767); that "the neural tradeoffs between amount and delay that are captured by the neurometric discount functions match the behavioral tradeoffs between these variables that are captured by the psychometric discount functions" (Kable & Glimcher, 2007, p. 1631); that "humans repeatedly combine prior and subsequent information as data accumulate over time," as reflected by ACC activity; and "that activity in the striatum during valuation of monetary gambles are nonlinear in probabilities in the pattern predicted by prospect theory, suggesting that probability distortion is reflected at the level of the reward encoding process" (Hsu et al., 2009, p. 2231). Despite these impressive results, it should be kept in mind that only different forms of neoclassical models were applied and compared, that is, competitive tests were carried out only within the same model class of as-if models. Moreover, these models were fit to the behavioral data (for problems with data fitting, see above), and the results cannot conclusively demonstrate that the respective activated regions implement the process specified within the model. In our view, however, it is a step in the right direction and should definitely be pursued and extended.

5. Taking stock: As-If models, small worlds and comparative tests

5.1. As-If models and neuroeconomics

In reviewing the neuroeconomic literature it appears that the overarching theoretical framework is the neoclassical as-if theory. The consensus that "the brain must perform multiple value computations to make sound choices" (Hare et al., 2008, p. 5623) just as in the as-if theory seems too strong and questionable given that hitherto only few studies investigated competing process models.

5.2. Small worlds and neuroeconomics

The majority of cognitive neuroscience studies on decision making use variants of small-world problems, prototypical gambling tasks, in which all alternatives, consequences and their probabilities are known. In nongambling decision situations, such as intertemporal choice paradigms, decisions are not even risky, but have certain outcomes. Examples are: "Do you prefer $24 now or $33 in 4 weeks?" or "How much are you willing to pay for a candy bar?" (cp. Hare et al., 2008; Kable & Glimcher, 2007; Lebreton et al., 2009; McClure et al., 2004; Plassmann et al., 2007). Moreover, in several other decision making and conditioning tasks, participants

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had extensive experience with the stimuli and the associated rewards, so that choice might simply have entailed assessing the likelihoods of rewards, as for example in probability-tracking tasks and their variants (cp., Behrens et al., 2007; Huettel et al., 2005). Subsuming conditioning under decision making is a questionable practice that leads to every response, conscious or unconscious, being called decision making, so that the term becomes meaningless. Accordingly, decisions such as whether to select surgery or radiation therapy for a tumor, to invest retirement savings in the stock market or treasury bills, to pursue a university degree, or to accept a new job – all of which were mentioned as prototypical for decision making (examples taken from Rustichini, 2009; Tom et al., 2007; Trepel et al., 2005) – have almost nothing in common with the experimental investigations of decision making processes in neuroeconomic studies (so far).

At this point, we return to Savage's distinction between small worlds and large worlds. Savage, the father of modern Bayesian decision theory, considered Bayesian rationality as normative for small worlds, holding the opinion that a decision maker should engage in subjective EU maximization when making decisions under risk in such a world. But Savage also wrote that it would be "ridiculous" to use Bayesian rationality outside small worlds. Instead, he emphasized that rational models cannot be automatically assumed to provide the correct answer in real-life decision situations. Large worlds need a different kind of rationality, and the study of heuristic decision making is one way to model rationality under uncertainty.

With that said, we agree with Glimcher (2009) that it might be the case that "dopamine neurons lead to the direct computation of SV [subjective value] under some conditions" (p. 514), whereby "some conditions" should be translated to "small-world problems". Although we believe that none of the proposed subjective EU maximization strategies is computationally feasible in large worlds, those who make the claim that dopamine neurons compute EU in small worlds need to show this by performing competitive tests with models that do not involve optimization.

A promising course of research, we think, is based on modeling cognitive decision making processes by means of alternative models, including models of heuristics, and testing and comparing their respective neural correlates.

Given that we share neuroscientists' overall aim of understanding how decisions are made, our main concern, however, is to promote the use of uncertain large-world paradigms in the neuroeconomic literature. For one, it is indispensable to incorporate heuristics into the theoretical portfolio, since previous research on large-world problems has shown that laypeople and experts (e.g., doctors, judges, managers) use heuristics in an ecologically rational way, that is, when the heuristics are adapted to the structure of the environment (Dhami, 2003; Gigerenzer & Gaissmaier, 2011; Gigerenzer et al., 2011; Wübben & Wangenheim, 2008). This research indicated that individuals, especially under time pressure and information overload, switch to simple noncompensatory strategies that use few cues rather than engaging in exhaustive compensatory strategies such as EU maximization.

5.3. Predictive and competitive tests and neuroeconomics

The inventory for this issue is elaborated in section 4. In short, neuroeconomics may do a good job of predicting BOLD signal changes as a function of the manipulation of the independent variable(s), but we hold that neuroeconomic studies have a large developmental potential for competitive tests, especially with regard to heuristic models. As outlined above, our second concern is to promote predictive and competitive tests as methodological standards in neuroeconomics (where it is feasible). For example, cognitive neuroscience investigations could compare different decision strategies that individuals actually used (cp. Venkatraman et al., 2009). Examples of general methodological approaches to determine which decision rules people (very likely) follow are the use of outcome-based strategy classification such as the maximum-likelihood strategy classification (Bröder & Schiffer, 2003; Bröder, 2010) or ACT-R (Anderson, 2007), cognitive process analysis (if it is useful) (Witteman & van Geenen, 2010), or a multiple measure strategy classification combining outcomes and decision times (Bergert & Nosofsky, 2006; Bröder & Gaissmaier, 2007; Glöckner, 2010; Rieskamp & Otto, 2006).

6. Conclusion

Neuroeconomics or the study of the neurobiology of decision making set out with ambitious aims, namely, "revealing the neurobiological mechanisms by which decisions are made" (Glimcher & Rustichini, 2004, p. 447) and "providing a biologically sound theory of how humans make decisions that can be applied in both the natural and the social sciences." (Rangel et al., 2008, p. 545). Back in 2005, Camerer, Loewenstein, and Prelec outlined two types of contributions that they suggested neuroscience could make to economics, or more broadly to decision sciences, namely, an incremental and a radical approach. The incremental approach was formulated as "neuroscience adds variables to conventional accounts of decision making or suggests specific functional forms to replace "as if" assumptions that have never been well supported empirically." (Camerer et al., 2005, p. 10).

We highly appreciate this statement, yet, as the previous literature review showed, in most neuroeconomic studies, the as-if models were not replaced (e.g., by models of heuristic decision making) but instead retained as descriptions of how the brain works.

The radical approach, on the other hand, is about neuroscience informing economic theory. According to Camerer and colleagues (2005), neuroscience "points to an entirely new set of constructs to underlie economic decision making. The standard economic theory of constrained utility maximization is most naturally interpreted either as the result of learning based on consumption experiences (which is of little help when prices, income, and opportunity sets change), or careful deliberation – a balancing of the costs and benefits of different options […]." (p.10). In this passage, the authors appear to be in line with us. First, they acknowledge that for most of our real-life decisions we cannot rely on an extensive learning history and thus cannot define priors (as necessary for Bayesian calculations), and second, they admit that the decision process as prescribed in (neo-)classical decision theory for actual flesh-and-blood human beings is simply intractable: "The variables that enter into the formulation of the decision problem are precisely the variables that should affect the decision if the person had unlimited time and computing ability." (p. 10). In this way, Camerer and colleagues seem to concur with Savage that small-world and large-world decision situations differ fundamentally and that the investigation of small-world experiments alone may produce unrealistic data having little relevance for understanding how the brain deals with the real world. Yet, as we have shown in this contribution, the study of optimization in small worlds is still the norm of present-day neuroeconomics.

We find the advent of neuroeconomics promising and hope that it will continue on its original course so that we can arrive at psychologically valid accounts of human decision making. This, in our view, is only possible if the neuroscience of decision making forsakes as-if theories, investigates decision making under uncertainty (large worlds) rather than only under risk (small worlds), and implements competitive testing that includes heuristic models.

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