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Towards a Theory of Revealed Economic Behavior: The Economic-Neurosciences Interface

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Synopsis: Based on recent findings from economics and the neurosciences, we present a conceptual decision-making model that provides insight into human decision-making and illustrates how behavioral outcomes are transformed into phenomena. The model may be viewed as a bridge between the seemingly disparate disciplines of neuroscience and economics that may facilitate more integrative research efforts and provide a framework for developing research agendas for scientists interested in human behavior and economic phenomena.

Key words: revealed behavior, decision-making model, predicting behavior, understanding behavior, economics, neurosciences, synthesis

JEL classification: A1, D1, E6, G1, M1, Q1

1. Introduction

'How far will economics have to travel to reach solid behavioral ground?'

Daniel McFadden (1999, pp. 1–3)

'But a scientific understanding of the human mind and human behavior in terms of brain function could also have a profound impact on how we understand ourselves and our society.'

M. James Nichols & William T. Newsome (1999a, p. C37)

Explaining economic behavior is challenging. Why does the stock market crash? Why are some countries poor? Why do we see extreme behavior after September 11, 2001 such as a reluctance to travel and stockpiling medicine (Schuster et al. 2001)? These are unanswered questions derived from a more basic question: What shapes the world? The answer is simple and complex: The behavior of humans. So, it seems natural to look at the decision-making process of humans to understand economic phenomena. Understanding individual decision-making behavior has received considerable attention in the economic literature. A major emphasis has been the study of rational decision-making. Various researchers have shown that rational behavior does not always coincide with actual behavior (Tversky & Kahneman 1981). This observation has triggered research within the economic discipline that often is referred to as behavioral economics (Thaler 1997). Behavioral economists explained anomalies, circumstances in which several assumptions of the 'economic' man are falsified due to less-than-full rational behavior (Camerer 1995, Lewin 1996, McFadden 1999, Rabin 1998).[1] However, their findings only seem applicable in narrowly defined situations (Rabin 1998, Thaler 1997). To better understand complex phenomena like poverty that are, among other things, the result of human behavior, one has to open the black box of the decision-maker's inferential machinery (Pennings & Garcia 2005). It seems therefore valuable for economists to look at the recent findings in neurobiology and neurophysiology that are beginning to discern how the brain transforms inputs (stimuli) into behavior (Nichols & Newsome 1999b, Platt & Glimcher 1999).

Based on recent research in economics and neurosciences, we develop a conceptual decision-making model that provides insight into the steps in human decision-making and how behavioral outcomes are transformed into phenomena. The framework is depicted diagrammatically interspersed with symbolic systems theoretic notation. The symbolic representation helps to formalize the arguments and output of the processes and to see decision making from reception of stimuli to actual behavior as a continuous and dynamic process in time t. The framework may permit us to identify where research is needed and as such provides a new research agenda for disciplines that study human behavior. Certainly, it should provide a platform to strengthen dialogue between economists and neuroscientists in this intriguing area.

2. Conceptual model

The conceptual model can be viewed as a simultaneous interactive process in which the decision-maker initially transforms stimuli to perceptions where perceptions reflect the interpretation of stimuli. These perceptions are, among other things, the input for the algorithm that decision-makers use to reach a choice. After gaining insight into behavioral outcomes, we look at the interaction among behavioral outcomes as this interaction also influences the individual decision-making

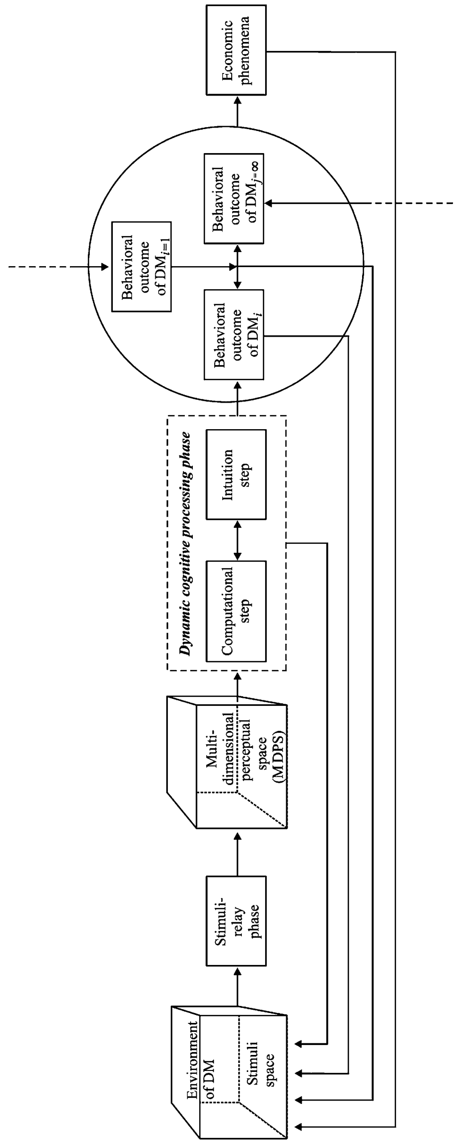

Figure 1. Conceptual model of individual decision-making processes and economic phenomena: an economic-neurosciences interface.

process, creating dynamics. The combination of behavioral interactions drives the phenomena of everyday life.

Figure 1 provides a general overview of the conceptual model. Figures 2 and 3 provide a more detailed depiction of the 'stimuli-relay phase' and the 'dynamic cognitive processing phase'.

Stimuli can be physical, such as pain and sun-light or can be a flow of information such as stock prices. These stimuli can be transformed into perceptions which provide an individual's interpretation of the information. Similar stimuli (e.g., the news that IBM sold a division) might result in different perceptions (IBM is losing market share by selling the division or IBM is earning money by the sale). Since decision-makers are often confronted with numerous stimuli, not all information is transformed to perceptions. In cognitive neuroscience, research has been performed on how various regions of the brain respond to stimuli and how information processing occurs (Waldrop 1993). Researchers have shown that the transformation process of signals to the rest of the brain is determined by the neural activity centered in the thalamus (Clayton 2000). The transformations of stimuli in the thalamus are critical for perceptions (Andersen et al. 1997). All stimuli are first relayed to a specific part of the thalamus before projecting them to specific locations in the cortex. In this way the thalamus functions as a filter and gatekeeper. These findings support the existence of a filter mechanism that coordinates which signals excite cells and are transformed to perceptions. This filtering stage allows selective processing of stimuli relevant to the current decision context (e.g., Figure 2). After each stimuli reaches the appropriate cortex, the actual perception of stimuli goes through the primary and then secondary sensory areas. The processing in the cortex is performed in a parallel manner. Cellular physiological techniques revealed that the traffic between thalamus and cortex is bidirectional (i.e., the thalamus also receives input from the cortex). The filtered stimuli that are transformed to perceptions fill the multi-dimensional perceptual space (MDPS) which is located in the posterior tertiary association cortex, the final destination for transformed stimuli. In this phase, the decision-maker must simplify high-dimensional data onto a low-dimensional structure. Tenenbaum et al. (2000) states, 'The human brain confronts the same problem (the problem of dimensionality reduction) in everyday perception, extracting from its high-dimensional sensory inputs—30 000 auditory nerve fibers or 10^6 optic nerve fibers—a manageable small number of perceptually relevant features'. Perceptions will be complemented by information the decision-maker has stored in his/her (working) memory. Long-term memory provides a reservoir of information, often obtained by experience.

The stimuli-relay stage can be expressed in symbolic language. Define:

$\Pi(t)$: the stream of stimuli a decision-maker confronts at moment t. The stream of stimuli that arrives to the brain consists of high dimensional information that varies widely in time. For instance, when sleeping reception is decidedly limited. The filtering operation is viewed as a mapping from high to a lower dimensional stimuli space that is affected by memory:

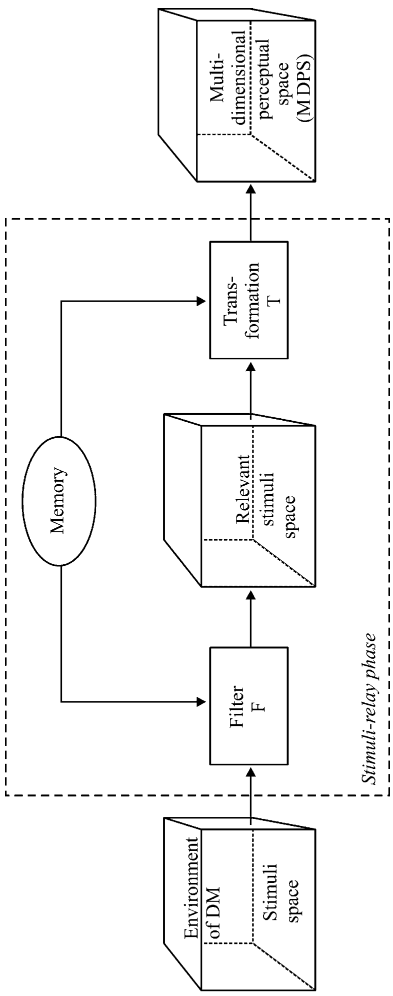

Figure 2. Transformation from stimuli to perceptions.

$$\mathrm{F}(\Pi(t), \mathrm{memory}(t)): \text{filter on stimuli.} \tag{1}$$

The evolution of memory and/or experience through time is a specific process where the input is the stream of relevant stimuli from the past to moment t. Its development is essential for the way a person deals with information and is a stock variable, a reservoir that stores experiences from the past. Memory is also used in the transformation process of the stimuli-relay phase:

$$\mathrm{T}[\mathrm{F}(\Pi(t)), \mathrm{memory}(t)]: \text{transformation of stimuli into perceptions} \tag{2}$$

The mathematical character of the stimuli space can be seen as a high dimensional vector space where the intensity of reception by the cells can take on specific values. Perceptions, because of their complexity, need to be viewed as higher dimensional objects which require abstract topological thinking to depict the character of their space. Regardless, the formed objects, the perceptions, stream into the MDPS based on the filtered stimuli.

The MDPS can be envisioned as the information space available to the decision-maker in order to develop a potential behavioral outcome that satisfies the decision-maker's objectives. Because the MDPS is very complex and the decision-maker has limited processing and computational capability, the decision-maker faces a difficult challenge.

Perceptions are transformed into a behavioral outcome in the Dynamic Cognitive Processing phase (DCP). (See Figure 3). The DCP phase consists of two steps that complement and interact with each other: a *computational* step and an *intuition* step. The *computational* step represents an analytical process in which the decision-maker relates perceptions to the decision-maker's *objectives* (Tremblay & Schultz 1999). Specifically, the decision-maker processes information (e.g., perceptions) to determine an alternative outcome that fits his (her) objectives.[2] These objectives are the expected rewards (e.g., utility) of a behavioral outcome (Platt & Glimcher 1999). Nichols & Newsome (1999b) suggest that when an animal decides between two alternatives, both the choice made and the neural activation in the lateral intraparietal cortex are correlated with the *expected reward*.

During the DCP phase, but particularly in the computational phase, three cortical association areas in the brain play a crucial role: the parietal cortex, the dorsolateral prefrontal area and a temporal area. The dorsolateral prefrontal area plays the highest executive function of the brain, choosing between alternatives and solving problems. All three areas interact and work together to achieve the executive function. The DCP phase involves weighing numerous factors and requires parallel activity in multiple networks of connections between the prefrontal cortex and other associated areas.

The computational step results in *behavioral outcome alternatives*. The behavioral outcome alternatives fill the *behavioral outcome space* (BOS). In the *optimization phase*, which is part of the computational step (e.g., Figure 3), under the influence

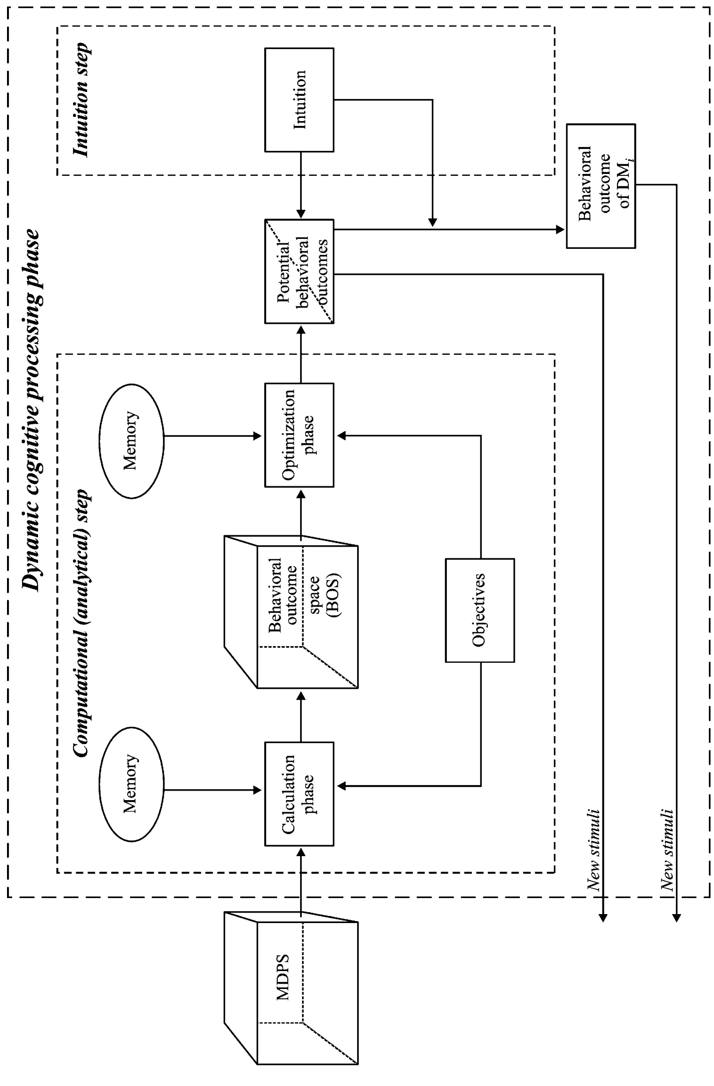

Figure 3. Dynamic cognitive processing: interaction of computational step and intuition step.

of memory, the BOS and the decision-maker's objectives are used to select *behavioral outcome alternatives* which become *potential behavioral outcomes*. The computational step approximates most closely economic modeling that describes human behavior based on mathematical programming models where objectives (utility) are optimized over a feasible set of alternatives. As such this is a convenient approach to describe rational behavior.

When focusing on the DCP of generating alternative actions and deciding on final behavior, we view its input to be a stream of perceptions $\Omega(t) \in$ MDPS. As noted, its structure deviates from standard vectorial numerical representation. In the calculation phase, algorithms are used to generate alternatives that gradually fill the BOS. This can be expressed as:

$$[\mathrm{BOS}](t) = \mathrm{Comput}(\Omega(-\infty, t]), \mathrm{memory}(t), \mathrm{objectives}) \tag{3}$$

Relevant objectives are used to value the alternatives, to distinguish what is feasible and what is not. From a multi-criteria perspective, one could say that the calculation phase generates constraints on and criteria values for alternatives. This makes it easier to consider the BOS as a set of numerical vectors that represent the potential alternatives, each element describing a value of a criterion (alternatively called attribute, goal or objective). Note that decisions to wait for more information or to allow more time for assessment of complex situations also are feasible alternatives.

The optimization phase weighs the alternatives and reduces their number. From a multi-criteria perspective, dominated and infeasible alternatives can be removed on an algorithmic, rational basis. The DCP phase also recognizes that alternatives may emerge from outside the rational process due to intuition.[3] In the optimization phase of the DCP alternatives are selected that maximize utility subject to BOS and intuition.

In symbolic language this leads to a potential behavioral outcome space:

$$\mathrm{Pot\ beh}(t) = \max(\mathrm{U}(\mathrm{c}(t)) \text{ subject to } \mathrm{BOS}(t), \mathrm{intuition}) \tag{4}$$

where we can think of Pot beh(t) as a set of alternatives at time t and where max stands for maximizing, U(.) is a well-defined utility function, c is the objective(s), and BOS and intuition are the constraints. The maximization procedure is a multi-criteria decision-making (MCDM) outranking procedure that eliminates the dominated actions and yields the Pareto (with respect to BOS) ones (Belton & Stewart 2002). Figure 3 depicts the computational step in a step-wise manner, which is an over-simplification from a neurological perspective since many parts of the brain are simultaneously involved during the computational step. Miller (1956) identified physiological limitations on the pace at which humans can process information. Recently, Vogel & Machizawa (2004) showed that although the human brain is acutely aware of the many objects in the world, people are only aware of three or four at any given time, demonstrating a direct relationship between brain nerve activity and memory capacity. Vogel & Machizawa (2004) and Todd & Marios

(2004) conclude that a person's working memory capacity is determined in the posterior parietal cortex. The notion that human's processing capacity is limited, led Simon (1955) to introduce the concept of bounded rationality. The concept states that the capacity of the human mind for formulating and solving complex problems is small compared to the size of the problems that need to be solved for objectively rational behavior to exist in the world.

The working memory in humans is considered vital to learning and reasoning, and hence, is fundamental for the computational step (Fischbach 1992). When information capacity limits occur we may expect that decision-makers will use more simple algorithms and rely on less formal processes, i.e., *intuition*, since such strategies require less information processing capacity. Intuition has been conceptualized in a number of ways. Khatri & Ng (2000) review some properties of intuition; intuition is subconscious, complex, quick, not emotion, not biased, and part of all decisions. Gehring & Willoughby (2002) showed how subconscious processes can affect behavioral outcomes. Here, we follow a definition proposed by Behling & Eckel (1991) where intuition is defined as a choice made without formal analysis. The definition identifies the difference between the computational step and intuition: the computational step is the analytical process, whereas the intuition process can be viewed as a latent process that is running in the 'background' of the decision-maker, requiring less processing capacity than the computational step. Agor (1984) and Parikh et al. (1994) showed that managers use and rely on intuition, particularly in decisions involving unstructured problems. In our framework unstructured problems refer to situations when stimuli do not result in clear and an unambiguous interpretations (e.g., perceptions are fuzzy), and/or objectives in the computational step are not well defined. Eisenhardt (1989, 1990) and Bourgeois & Eisenhardt (1988) showed a significant contribution of intuition to the increased speed of decisions. We expect that intuition complements and interacts with the computational step, providing extra 'fuzzy' information to the MDPS and/or the decision-maker's objectives. This extra information may change the potential behavioral outcome generated in the computational step. Furthermore, intuition may be more concrete and lead to the development of alternative potential behavioral outcomes. The feeling that 'I know that I should choose A, but my gut tells me to choose B′ may reflect such a situation. The notion of interaction between the two steps is supported by Zeki (1992) where he shows that information (e.g., perception) does not travel along a single pathway, rather different features of a single perception are processed in parallel pathways.

As visualized in Figure 3, the result of the interaction between intuition and the potential behavioral outcomes generated in the computational step is a *behavioral outcome*: an action of the decision-maker. In symbolic language,

$$\mathrm{Beh}(t) = \mathrm{Ints}(\mathrm{Pot\ beh}(t),\ \mathrm{intuition}) \tag{5}$$

where Ints maps from the set of alternatives to Beh(t) the observable behavior at time t.

To this point, we have described the stimuli-relay phase and the DCP phase as being sequential, that is first the stimuli-relay phase occurs followed by the DCP phase which can feed back to the stimuli-relay phase. However, we may expect that both phases are performed by the decision-maker in concert. That is, the decision-maker uses perceptions in the DCP phase while at the same moment filtering stimuli and giving interpretations to the stimuli (e.g., perceptions).

The DCP phase may require more information, and lead the decision-maker to use information in the memory or reconsider several stimuli. Further, since there is a continuous stream of stimuli and choice problems are rarely confronted in isolation, decision-makers generate numerous behavioral outcomes in a parallel manner. For each of these behavioral outcomes the decision-maker performs the stimuli-relay phase and the DCP phase outlined above. The decision-maker might use the same algorithm for different tasks, but some behavioral outcomes may be more driven by the intuition step while others may need to be solved in the computational step. Based on bounded rationality (Simon 1955), we hypothesize that the capacity of the human mind for solving complex problems determines whether the potential behavioral outcomes are mainly driven by the computational step or by intuition. If the capacity of the human mind is relatively small (large) compared to the size of the problem that need to be solved, intuition (computational step) may be the main driver. Further, sometimes choices are made unconsciously because they are routine. This means that these choices are driven more by intuition as decision-making processes use 'fixed' algorithms to solve repetitive problems. New or complicated problems may require the use the computational step of the DCP phase intensively and require considerable processing capacity.

Decision-making is a dynamic and continuous process. Interactions and feedbacks between the processes used to solve different problems are likely to occur. Perceptions, algorithms or behavioral outcomes from decision process A might be used as input in decision process B. Hence the decision-maker's behavioral outcome generation process is not smooth, and outcomes may appear chaotic and not structured. Further, behavioral outcomes of a decision-maker interact with behavioral outcomes of other decision-makers. This interaction or reaction may result in new stimuli and hence a new round of the decision process (Mace 2000, Nash 1950).The results of the interactions of decision-makers' behavioral outcomes and the institutions (rules of the game) that themselves are human constructs, are the economic phenomena in society (inflation, stock market crashes, etc.). Human social interactions are also influenced by 'social intelligence'. An important component of social intelligence is the capacity to understand and manipulate the mental states of other people and thereby to alter their behavior (Frith & Frith 1999). In our model, these social interactions provide further simuli to decision-makers. Whether these stimuli will become a perception again depends on the 'stimulus filter mechanism'.

3. Discussion

Arthur (1999) recently portrays economic phenomena as process dependent, organic, and always evolving. Economic agents react to each others' behavior and by doing so the aggregate (phenomena) changes. In turn, as the aggregate changes, the behavior of economic agents changes in response to these new stimuli, resulting in a constantly changing economic environment. Economic agents do not react in a similar, pre-determined manner, instead choosing to respond strategically by considering the possible outcomes that may result as a consequence of their behavior. Nevertheless, in certain circumstances, where experiences and aspirations are in common, and where the solution to the problem is direct such as in impersonal markets, standard economic models may do a reasonable job of describing and predicting outcomes. However, the usefulness of these models in explaining and predicting behavior declines as the complexity of the economic phenomena increases and decision-makers' experiences objectives, and constraints become more heterogeneous.

The proposed model, as reflected in Figures 1–3, may foster a better understanding and may give new insights into perplexing problems. For example, from a neurological perspective behavioral outcomes are driven by the interaction of neurons in the brain (Platt & Glimcher 1999). Mayford et al. (1996), among others, show that the anatomical connections between neurons develop according to a definite plan, but their strength and effectiveness are not predetermined and can be altered by experience. That is, the structure of the decision-maker's decision-making process may change over time. This offers an explanation to the ever-changing world. Similarly, a topic that appears to puzzle many of us is poverty. Although the western world has experienced booming economies and an unprecedented technological revolution, billions of people are living in poverty and numerous people are dying each day as a result of poor conditions. Why are people poor? Can we begin to resolve this problem by a better understanding the decision making process? The proposed model might contribute to answering these questions by providing a framework for researchers to identify how the structure of decision making may vary across different individuals, groups or cultures (e.g., Pennings & Garcia 2004). Furthermore, the institutions in society, which are a product of human behavior, play an important role in understanding economic phenomena. Hence economists may be able to use the framework to structure their research questions to analyze the complex interactions that cause economic phenomena. At the same time, neuroscience may benefit from the proposed framework as it models the brain as an economic system with goals and constraints in order to predict both how behavior is generated (i.e. pathways) as well as behavior itself (Glimcher 2003).

Above all, our framework may be seen as a bridge between seemingly disparate disciplines that may permit more integrative and useful research efforts. In this context, its use can help us relate theories across disciplines. For example, Elliott et al. (2000) studied the neural responses of subjects participating in a gambling task similar to the experiments done by Tversky & Kahneman (1981). They found increased activity in the right midbrain regions and the right ventral striatum when individuals were winning, and an increased activity in the hippocampus and parahippocampus when subjects were losing. Prospect theory shows that decision-makers are risk averse when winning and risk seeking when losing. Breiter, et al. (2001) further elaborated on relating brain activity and prospect theory when they mapped human hemodynamic responses to the expectation and experience of monetary gains and losses. They found that a broadly distributed set of brain regions was activated during the prospect phase and that these regions were also activated during the outcome phase. Questions immediately emerge: Are risk aversion and risk seeking behavior determined by specific regions in the brain? Are differences in risk attitude, which research suggests is context specific, a result of specific activation of different sites in the brain?

Similarly, the framework may provide a guide to develop research agendas of scientists who are interested in human behavior and economic phenomena. For example, preference reversals are one of the most impressive puzzles in the economic literature. In this puzzle, the decision-maker changes his/her decision without new information. A classical example is the individual who chooses gamble A over B (or B over A) but then states that his/her minimum willingness-to-accept price for A is less (more) than the minimum willingness-to-accept price for B (Safra et al. 1990). Such choice revealed preference reversals have been detected in several empirical studies. Grether & Plott (1979) asked the following two questions: Do preference reversals exist in a situation where economic theory is generally applied? Can preference reversals be explained by applying standard economic theory or some related construct? In their experiments, which closely followed the 'gamble choice experiment' described above, they controlled for the factors that had been proposed as explanations for the preference reversals, such as misspecified incentives, income effects, unsophisticated subjects, etc. Although they controlled for all the economic-theoretic explanations of the phenomenon, they had to answer the first question with a clear yes and the second with a clear no. Our model might suggest that the interaction between the computational step and the intuition step in the DCP phase might cause this effect. In some instances the potential behavioral outcome generated by the computational step may be 'overridden' by the behavior outcome generated by the intuition step causing these phenomena of preference reversals. When and how does this happen? Economists may think of a framing effect (i.e., the nature of the decision context) while neuroscientists may be think of information that is processed in parallel pathways in the brain (Pennings & Smidts 2003, Tversky & Simonson 1993, Williams & Stuart 2002). This example suggests that if we want to understand how the world is shaped and if we want to exercise influence on this shape, economists and neuroscientists should work closely together. This notion is further substantiated by the recent findings of Smith et al. (2002) who found, using positron emission tomography, that the brain does not honor a prevalent assumption of economics: the independence of the evaluations of payoffs and outcomes. The proposed model is a step to bridge these seemingly distant disciplines, and can be viewed as a research structure to which both economists and neuroscientists can relate, thereby enhancing the integration of these two disciplines.

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Notes

1. We do not review the immense literature on decision-making behavior exhaustively; Lewin (1996) presents an excellent overview. Neither do we review the debate between economists and psychologists on decision-making behavior (e.g., Camerer 1995, Rabin 1998).
2. Note that we do not assume all decision-makers to have the same objectives. Objectives can be defined on a local level, getting to Chicago in the fastest way, or on a very abstract level, do good for the world.
3. Intuition is defined as a choice made without formal analysis.

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