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Decision making in uncertain times: what can cognitive and decision sciences say about or learn from economic crises?

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> 'The essence of the situation is action according to opinion, of greater or less foundation and value, neither entire ignorance nor complete and perfect information, but partial knowledge. If we are to understand the workings of the economic system we must examine the meaning and significance of uncertainty; and to this end some inquiry into the nature and function of knowledge itself is necessary'
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> Frank H. Knight, *Risk, Uncertainty, and Profit*, 1921

Economic crises bring to the fore deep issues for the economic profession and their models. Given that cognitive science shares with economics many theoretical frameworks and research tools designed to understand decision-making behavior, should economists be the only ones re-examining their conceptual ideas and empirical methods? We argue that economic crises demonstrate different forms of uncertainty, which remind cognitive scientists of a pervasive problem: how best to conceptualize and study decision making under uncertainty.

The challenge: uncertainty in various (dis)guises

Economic crises illustrate various types of real-world decision making under uncertainty within dynamic environments. These decisions involve dependencies in time and interdependencies amongst multiple agents [1] For instance, investors need to decide whether to provide loans to governments and banks without knowing how markets will develop and what policy makers will decide to do. Politicians weigh up the decision to bail out fragile banks and countries, while at the same time trying to appease the interests of their electorate. Here we can see that uncertainty is an inherent feature of the decision environment and of the agent (e.g., limitations in knowledge and information-processing capacities, conflicting goals). Uncertainty permeates all aspects of real-world decision problems, from constructing the action and outcome space to inferring the probabilities and values of outcomes and predicting the behavior of others. The question is, how can we best conceptualize decision making under uncertainty in all these various (dis)guises? More to the point, how can we characterize the many forms of uncertainty with which people have to cope in the real world?

Taking stock of the canonical framework for decision making

The canonical approach for conceptualizing decision making builds on the idea that possible states of the world can be associated with subjective probabilities and values (Box 1). In this view, all forms of decision making conform to two fundamental principles: (i) a trade-off between outcome probabilities and values, used to derive the expected utility of alternative actions; and (ii) decision makers act *as if* they maximize subjective expected utility (SEU) [2]. Although empirical research has revealed several departures from SEU theory, enriched variants try to take into account the peculiarities of human decision making, while preserving the core principle of utility maximization [3].

So, to what extent can this approach be used for understanding decision making in real-world contexts? Let us take the problem of investors deciding on whether to buy bonds from a struggling eurozone country. SEU would propose that investors consider the probability and value of future events, such as the risk of default. However, we already face a stumbling block: where do the probabilities come from? Unpacking this question involves turning to an economically informed distinction between different types of decision situations based on the agent's sources of knowledge regarding outcomes and probabilities. Knight [4] distinguished between: (i) *a priori* probabilities, which can be logically deduced, as in games of chance; (ii) statistical probabilities, derived from data; and (iii) estimates, arising from situations in which 'there is no valid basis of any kind for classifying instances' ([4], p. 225). Here, then, decision making under risk refers to situations in which probabilities are known (or knowable), whereas situations of uncertainty are characterized as cases where probabilities are neither logically deducible nor can be inferred from data. For instance, investors cannot refer to data to assign probabilities and value estimates to the consequences for the eurozone if a member defaults; therefore, decisions will only ever be based on (Knightian) estimates.

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Box 1. The canonical framework for decision-making research

Rational choice theory. The canonical framework of decision making is based on two assumptions. First, the agent can order all possible situations according to her preferences; second, she always acts in accordance with them. Under some mild assumptions, this is equivalent to maximizing expected utility. In practice, however, specifications are required about what matters in such preferences, such as monetary or social welfare (e.g., Mother Theresa can be conceptualized as a perfectly rational agent by assuming that her utility function is based on the interests of the poor and sick).

Subjective expected utility (SEU) theory. The goal of SEU theory [2] is to give content to such preferences in the case of uncertainty. Agents are assumed to have preferences between actions, $a \in A$, from which the decision maker can choose. These preferences depend on possible states of the world, $s \in S$, which are beyond the agent's control, and 'consequences' or outcomes that she will eventually face. Savage showed that, under some arguably reasonable conditions, agents would choose acts as if they ascribed probabilities to states of the world and utilities u to consequences and maximized the corresponding expected utility, given by:

$$SEU(a) = \sum_{s \in S} p(s)u(a(s)) \qquad [1]$$

Fundamental to this framework is the result that act a is preferred to act a' iff and only if the expected utility of a is larger than that of a'; that is, $a > a'$ iff $\mathrm{SEU}(a) > \mathrm{SEU}(a')$.

Expected utility and subjective expected utility. SEU can be seen as a generalization of expected utility theory as formalized by von Neumann and Morgenstern in 1944. This is decision making under risk, because the objective probabilities are known. Formally and operationally, the results have similar implications (i.e., the maximization of expected utility). However, at the conceptual level, Savage's theory is often interpreted as the origin of the applicability of expected utility theory for decision making under uncertainty, because it derives the existence of subjective probabilities from conditions on an agent's preferences.

Generalization of (subjective) expected utility theory. The descriptive accuracy of expected utility theory has been challenged by several empirical studies (e.g., the Allais and the Ellsberg paradox). The framework has been adapted to account for these findings through 'generalized' expected utility, which assumes the maximization of uncertainty-weighted expected utility (e.g., with a transformation of probabilities) and the separate representation of uncertainty and consequences of actions through probabilities and utility [3].

Although the distinction between risk and uncertainty is intuitively plausible, defenders of SEU have dismissed the risk/uncertainty distinction, arguing that the canonical framework assumes that decision makers act 'as if they assigned numerical probabilities to every conceivable event' ([5], p. 282). Thus, the claim is that people act rationally, given their subjective – not necessarily veridical – beliefs, with subjective probabilities and utility functions serving as building blocks for modeling decision making.

Others take the Knightian distinction between risk and uncertainty as a starting point for considering alternative ways to conceptualize decision making. They start from the view that many real-world problems are ill-structured and not easily formalized and that humans are cognitively constrained in their ability to process the informational complexities that arise (i.e., real-world agents are boundedly rational) [6]. As a consequence, heuristics and approximate strategies are used in decision making under uncertainty [7,8]. For instance, when dealing with dynamic decision problems and the need to achieve long-term goals, an aspiration level-based strategy may be used that does not require precise quantitative knowledge of the decision environment [9].

Rethinking decision making under uncertainty

Although there is considerable dispute about both the general usefulness of the risk versus uncertainty distinction and the ways by which decision making is modeled, these differences are not necessarily reflected in the empirical tools. Typically, researchers use decontextualized situations with well-defined probabilities and outcomes, such as lotteries and experimental games. Presenting participants with the probabilities and payoffs enables researchers to control the epistemological states of the decision maker, which in turn allows her to use SEU-like models as the normative benchmark. However, this approach limits the insights that can be gained for understanding decision making under (Knightian) uncertainty. If probabilities and values are given, there is no possibility of examining important predecisional processes. For instance, when it comes to applying SEU-like decision strategies, researchers cannot explore how people come up with probability estimates and outcome values. Alternatively, if we assume that people might use strategies other than SEU-like ones, there is no way of examining which pieces of information (other than probabilities and outcome values) people use to reach a decision. The upshot here is that the empirical tools are often too constrained to examine whether decision making under uncertainty is qualitatively different from decision making under risk. The implication is that, if there is a qualitative difference, there is a fundamental limit to any generalization of current models of decision making beyond the laboratory to real-world decision-making situations.

Although these problems are often recognized, empirically studying decision making in uncertain environments that approximate those in the real world is anything but trivial. However, some steps have been taken in this direction; for instance, by using dynamic decision-making tasks that set up microworlds, with various interdependencies of decisions in time and between multiple variables or agents [1,9]. Moreover, in economics too there is a growing trend to move away from traditional risk-based paradigms (i.e., lottery-type tasks) by employing a richer combination of tools [10,11] or by conducting field studies to examine decision making under out-of-the-laboratory conditions [12].

A major stumbling block for broadening the empirical scope is the lack of a clear framework for conceptualizing uncertainty in all its various forms. Knight's uncertainty category is essentially a negatively defined concept; namely, the absence of an objective basis for inferring probabilities. This is a helpful starting point, but refinement is needed. Some researchers have recently expanded on Knight's formulation and proposed different levels of uncertainty that consider the relationships that uncertainty

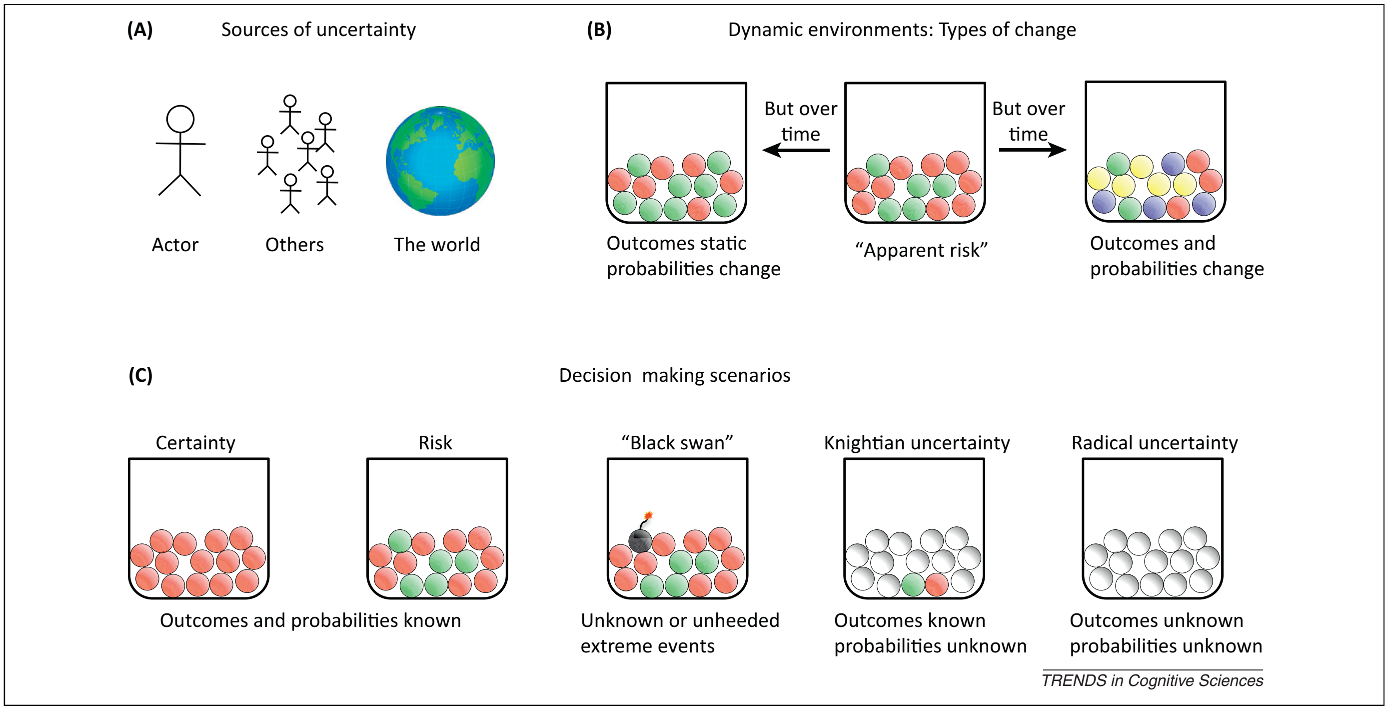

Figure 1. Uncertainty in its various guises. Illustrating sources of uncertainty and situations of decision making under uncertainty, using an urn model. (**A**) Uncertainty can reside in the mind of the boundedly rational agent. Uncertainty can also result from the decisions of and influences from other agents and from genuine randomness in the external environment (i.e., the data-generating process). (**B**) Examples of dynamic environments that involve changes in the decision-making situation over time. Left: The proportion of balls changes in unpredictable (or unknown) ways over time; therefore, probability estimates obtained at t_1 are of little use at t_2. Right: The outcomes themselves change over time, requiring a reformulation of the decision situation. (**C**) Examples of decision-making scenarios. From left to right: In situations of certainty and risk, the outcomes and their probabilities are known. In a 'black swan' situation, the urn contains a rare but highly consequential event (a 'bomb' or, in the case of a positive event, a 'diamond') that is either unknown to the decision maker or ignored in the representation of the decision situation. In a situation of Knightian uncertainty, the outcomes are known but not their probabilities. The right-most example is a situation of radical uncertainty, in which both the outcomes and their probabilities are unknown.

has to risk (e.g., whether we can reduce uncertainty to risk by sufficient amounts of data or whether even an infinite amount of data would be insufficient, because the data-generating process changes in unpredictable ways) [13]. Other authors have discussed variants of uncertainty from the perspective of inductive inference. They elaborate on problems arising from a misspecification of the hypothesis space (i.e., when the model used to derive predictions does not match the structure of the decision environment); this highlights breakdowns when applying models for situations of risk ('small worlds') to situations of uncertainty ('large worlds') [8,14].

We argue that real-world problems are a useful basis for characterizing variants of uncertainty and the types of uncertain environments with which decision makers (and cognitive systems in general) have to cope (Figure 1). For instance, economic crises illustrate uncertainty about the underlying dynamics of the conditions under which the decisions are being made, uncertainty in the feedback from decisions, uncertainty from interpreting the decisions and actions of multiple agents, and uncertainty in resolving conflicts between competing goals [1,9]. One may dispute whether the ultimate goal for theoretical and empirical research is to explain how decisions are made in complex real-world situations, where all of these uncertainties prevail, or whether the goal is to pinpoint characteristics of environmental structures to explain adaptive behavior and cognition. In any case, a first and necessary step is to identify types of uncertainty that can guide and expand theoretical and empirical practices.

Concluding remarks: coping theoretically and empirically with uncertainty

Our starting point was the claim that real-world problems like economic crises highlight the potential limitations in the way decision-making behavior is usually conceptualized in both economics and the cognitive sciences, particularly with respect to the many forms of uncertainty that people face outside the laboratory. In our view, the major challenge for developing a more comprehensive theory of decision making is the lack of a classification system that captures key elements of uncertainty and uncertain environments. If serious attempts are made to extend Knight's original formulation of uncertainty and develop a taxonomy of uncertainty to which researchers could adhere, perhaps this may shift the focus away from questions concerning the forms of rationality (or optimality) that decision-making behavior takes and onto questions about how best to conceptualize uncertainty in its many forms. This will not only provide a better foundation for modeling and studying decision making, but also set the stage for developing ways to aid decision makers when faced with real-world uncertainty [Haldane, A. (2012) *The dog and the frisbee*. Speech given at the Federal Reserve Bank of Kansas City's 36th economic policy symposium 'The Changing Policy Landscape', Jackson Hole, Wyoming. (http://www.bankofengland.co.uk/publications/Pages/speeches/2012/596.aspx)].

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References

1 Osman, M. (2010) Controlling uncertainty: a review of human behavior in complex dynamic environments. *Psychol. Bull.* 136, 65–86

2 Savage, L. (1954) *The Foundations of Statistics*, Wiley

3 Starmer, C. (2000) Developments in non-expected utility theory: the hunt for a descriptive theory of choice under risk. *J. Econ. Lit.* 38, 332–382

4 Knight, F.H. (1921/2006) *Risk, Uncertainty and Profit*, Houghton Mifflin

5 Friedman, M. (1962/1976) *Price Theory: A Provisional Text*, Aldine

6 Simon, H. (1991) Invariants of human behavior. *Annu. Rev. Psychol.* 41, 1–19

7 Gigerenzer, G. and Gaissmaier, W. (2011) Heuristic decision making. *Annu. Rev. Psychol.* 62, 451–482

8 Brighton, H. and Gigerenzer, G. (2012) Are rational actor models "rational" outside small worlds? In *Evolution and Rationality: Decisions, Co-operation, and Strategic Behavior* (Okasha, S. and Binmore, K., eds), pp. 84–109, Cambridge University Press

9 Selten, R. *et al.* (2012) Dealing with dynamic decision problems when knowledge of the environment is limited: an approach based on goal systems. *J. Behav. Decis. Making* 25, 443–457

10 Janssen, M.A. *et al.* (2010) Lab experiments for the study of social-ecological systems. *Science* 328, 613–617

11 Abdellaoui, M. *et al.* (2011) The rich domain of uncertainty: source functions and their experimental implementation. *Am. Econ. Rev.* 101, 695–723

12 Levitt, S.D. and List, J.A. (2009) Field experiments in economics: the past, the present, and the future. *Eur. Econ. Rev.* 53, 1–18

13 Lo, A.W. and Mueller, M.T. (2010) WARNING: physics envy may be hazardous to your wealth. *J. Investm. Manag.* 8, 13–63

14 Taleb, N. (2007) *The Black Swan: The Impact of the Highly Improbable*, Penguin

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