Mousavi, S., Meder, B., Neth, H., & Kheirandish, R. (2017). Heuristics: fast, frugal, and smart. In Morris Altman (Ed.), Handbook of Behavioral Economics and Smart Decision-Making: Rational Decision-Making within the Bounds of Reason (pp. 101-118). Cheltenham: Edward Elgar Publishing.

6 Heuristics: fast, frugal, and smart

Shabnam Mousavi, Björn Meder, Hansjörg Neth and Reza Kheirandish

> Recent years have seen important new explorations along the boundaries between economics and psychology. For the economist, the immediate question about these developments is whether they include new advances in psychology that can fruitfully be applied to economics. (Simon 1959, p. 253)

INTRODUCTION

Individuals often make smart decisions despite the inherent limitations of cognitive and material resources. Whereas mainstream economics has focused mainly on the allocation mechanisms of material resources by cognitively unbounded (fully rational) agents, behavioral economics aims to include allocation of cognitive resources by using the insights from the heuristics and biases program in psychology (Kahneman et al. 1982). In this chapter, we introduce another psychological program with a more optimistic perspective inspired by Simon's view of bounded rationality and developed systematically in the study of fast-and-frugal heuristics (Gigerenzer et al. 1999).[1] We make a distinction between human decision making in two situations: under uncertainty, in which case we reason that simple heuristics are successful strategies, and under risk, in which case we discuss the enhancing role of risk literacy and statistical thinking (for the ways in which information is processed and knowledge created under risk versus under uncertainty, see Mousavi and Gigerenzer 2014, Table 1; and for the realms of rationality see Neth and Gigerenzer 2015, Table 1). Our goal is to make sense of smart and efficient decision-making processes demonstrated by individuals who use their evolutionary developed and learned capacities.

Which recent advances in psychology are important to economic theory and behavioral economics? This chapter has emerged from a series of dialogues between two psychologists and two economists exchanging views on the study of fast-and-frugal heuristics as it pertains to the methods of understanding economic behavior and decision making. Our discussions developed before a backdrop of what we view as the thrust of our fields as well as their overlaps in relation to formal treatments of human behavior. What economists now practice and profess as the basis and criterion for rigorous study of economic behavior traces back to the normative interpretation of subjective utility.[2] Psychologists, by contrast, have often searched for systematic patterns of behavior in laboratory and case studies, often formulating models without subscribing to or aiming for accordance with universal maxims of behavior. The heuristics and biases research program (Tversky and Kahneman 1974) commenced with an inquiry into uncovering general cognitive mechanisms. Mainstream behavioral economics has combined the findings of this psychology program with the maxims of economics. The resulting body of work has been valuable in

Table 6.1 Ecological rationality and heuristics à la Smith (economics) and Gigerenzer (psychology)

<table>
<tr><th>Fast-and-frugal heuristics program</th><th>Constructivist versus ecological rationality in economics</th></tr>
<tr><td>A heuristic is ecologically rational to the degree that it is adapted to the structure of an environment
Humans have to adapt to a social and physical world, not to systems with artificial syntax, such as logic</td><td>Ecological rationality is concerned with adaptations that occur within institutions, markets, management, and social and other associations governed by informal or formal rule systems</td></tr>
<tr><td colspan="2">Overlap between psychology and economics: same definition of ecological rationality, when heuristic can be replaced by markets, management, or other rule systems
Research questions for behavioral economics: what is the relationship between rule systems and heuristics? Do they overlap, or is one nested in the other? What can be learned from establishing such characterizations?</td></tr>
<tr><td>Unbounded rationality can generate optimal solutions for simple situations, e.g., tic-tac-toe; omniscience and omnipotence can also be used for theoretical examination of human behavior, but applying them as universal standard of rationality is a scientific error</td><td>Constructivism or reason provides a variety of ideas to try out but often no relevant selection criteria, whereas ecological process selects the norms and institutions that serve the fitness needs of societies</td></tr>
<tr><td colspan="2">Overlap between psychology and economics: Norms produced by unbounded or constructivist rationality are not useful as selection criteria in complex situations; the ultimate evaluation comes from the real world, not from theoretical sophistication
Research questions for behavioral economics: In the study of human behavior where does realism matter, and where does it not? If norms are chosen conditional to the situation, how can we judge across situations? Can ecological fitness be formalized?</td></tr>
<tr><td>Experimental games are bound to study social behavior as rule-obeying behavior and not as rule-negotiating or rule-changing behavior</td><td>Observing how people actually behave reveals unanticipated system rules, e.g., hubs emerged unexpectedly (like an equilibrium) when airlines were deregulated</td></tr>
<tr><td colspan="2">Overlap between psychology and economics: rules are to be discovered as they emerge from social behavior. Formal models can be used to provide a possible description of what was observed
Research questions for behavioral economics: to what extent can field experiments improve the relevance of solution concepts used for the study of human behavior and specify their limitations?</td></tr>
<tr><td>Fast-and-frugal heuristics are strategies triggered by environmental situations and enabled by evolved or learned capacities</td><td>Heuristics are a kind of cognitive capacity that we can access, although we are not completely aware of our access to it</td></tr>
<tr><td colspan="2">Overlap between psychology and economics: The choice of heuristic strategy is often not fully deliberate. This does not exclude the possibility of training or altering the trigger conditions
Research questions for behavioral economics: When is a heuristic successful, and when does it fail? In real-world situations, when is it not rational to be 'rational'?</td></tr>
</table>

Source: Based on interviews in Mousavi and Kheirandish (2014).

whereas logic is content-free. Extending on this point, Mousavi and Gigerenzer (2011, p. 102) argue that 'cognitive scientists studied judgment errors in order to discover rules that govern our minds, just as visual errors were studied to unravel the laws of perception. This practice has generated a long list of so-called cognitive biases, with disappointingly little insight into how the human mind works'. Alongside Smith (2008, p. 31), we find that '[t]he failed objective of this constructivist adventure is cause for joy, not despair'.

Behavioral economics is concerned with making sense of human behavior, with the goal of developing a framework for analyzing decision-making in real-world situations, and evaluating and predicting human choice and actions therein. Vernon Smith's following remark refers to these tasks directly: 'Whatever it is that people do, it is evident that they do not think about the problem the way an economist does, nor do they model it that way' (Mousavi and Kheirandish 2014, p. 1784). As Gigerenzer elaborates, 'the question is not whether it is good or bad to ignore information but what ignoring information does psychologically . . . "Why a certain strategy?" and "When does it work?" rather than assuming "It maximizes something," and that something may be psychological' (Mousavi and Kheirandish 2014, p. 1784). This view, which emphasizes the interplay between heuristics and environments, and relies on the notion of ecological rationality to evaluate the rationality of human behavior, provides an alternative way for understanding our adaptive minds where constructivist rationality reaches its limits.

HEURISTICS AS ADAPTIVE TOOLS FOR DECISION MAKING UNDER UNCERTAINTY

A prevalent view in both psychology and behavioral economics, the heuristics and biases program (Tversky and Kahneman 1974), presumes that heuristics result from a trade-off between accuracy and effort and lead to flawed and biased thinking. Typically, the benchmarks used to corroborate these claims are formal frameworks such as logic, probability theory, and expected utility theory. These are presumed to provide normatively correct solutions, and deviations in human decision making constitute errors. We advocate a different view based on formal models of heuristics. Within the framework of fast and frugal heuristics (Gigerenzer et al. 1999), *heuristics* are adaptive tools that ignore information to make fast and frugal decisions that are accurate and robust under conditions of uncertainty (Neth and Gigerenzer 2015).

Heuristics are successful when they exploit an ecologically rational match to the structure of information in the environment. In the previous section, we discussed the role of ecological rationality in understanding the success of simple individual and organizational strategies in the juncture of psychology and economics. Here, we turn our focus to two central concepts in the theory of decision-making, namely, uncertainty and knowledge.

The path towards making a decision starts with a disequilibrium that triggers a search for solutions through processing information to create the knowledge we need (Dewey 1938 [1986]). Traditionally, we model this procedure in two forms, deductive and inductive, depending on the structural properties of the situation to be resolved (Goldman 1988). Also, we acknowledge the unknowns of the situation by specifying alternatives, consequences, and their probabilities, which leads to a characterization of the risk associated with the problematic situation. The way in which a problematic situation is crossing disciplinary boundaries, inspiring scientific inquiry into untapped domains and generating potential for further discoveries. At the same time, like any other field of study, behavioral economics has carried baggage from its mother discipline, which generated byproducts and implications for methods of research. Our assertion is that the study of the ecological rationality of fast-and-frugal heuristics (Gigerenzer et al. 1999) can provide important insights and tools for alternative and complementary analyses of behavior.

The framework of fast-and-frugal heuristics can be distinguished from the heuristics and biases approach by the following characteristics and standpoints. In our view, heuristics are indispensable strategies for successfully dealing with uncertain situations in the real world. Notably, most real-world situations do not allow identification of all alternatives, consequences, and probabilities, even subjectively, as required for finding the optimal solution. Moreover, the best solution from a social perspective does not necessarily accord with rational choice based on self-interest (for example, public goods). For these reasons, smart decision makers regularly develop and use heuristics, relying on the wisdom and experience that simple heuristics can outperform supposedly optimizing strategies in uncertain situations. More often than not, satisficing with respect to a good enough aspiration level turns out to be both rational and smart for boundedly rational agents. It is thus not irrational but intelligent to be less than fully rational, in the neoclassical sense, in many decision-making situations.

A two-way influence and exchange between psychology and economics can build upon shared notions such as ecological rationality of simple heuristic strategies. This is the core around which we have structured this chapter. We start with juxtaposing economic and psychological views of ecological rationality (based on interviews with Vernon Smith and Gerd Gigerenzer, both leading researchers in their respective fields), pointing out the overlaps between the two views, and then extend questions pertaining to behavioral economics as a set of suggestions for advancing the dialogue between economics and psychology. Viewing heuristics as adaptive tools for decision making is discussed next. Although heuristic strategies can be used both under uncertainty and under risk, the simplicity of heuristics makes them particularly successful under the irreducible uncertainty of many decision situations. This point is illustrated by connecting the Knightian distinction between risk and uncertainty to inferential rules, amended by heuristics. The practical success of simple heuristics is then illustrated in the domains of financial investments and business decision-making. Next, we consider potential implications of ecological rationality in two applied scenarios: the current debate on nudging and the use of natural frequencies in risk communication. We close by providing a brief summary and extending our collaborative challenge to economists.

WHERE ECONOMIC RATIONALITY MEETS PSYCHOLOGY

In his Nobel Prize lecture, Vernon Smith (2002) focused on two forms of rationality in economics and their functions with respect to the understanding of human behavior. The first form is constructivism, which is rooted in Hume's and British empiricism; here the study of human behavior starts with observing an outcome and then reconstructing the steps with which such an outcome can be generated through a deliberate reasoning process. This reconstruction provides a variety of possibilities and options to choose from, which are not sufficient for the realization of action. For that reason, Smith points out that 'constructivism alone leads nowhere; its roots must find ultimate nourishment outside of [such] reason. Outside means knowledge derived from experience, from social interactions, and from unconscious sources and processes – the nexus that I have called ecological rationality' (Smith 2008, p. 287). Interestingly, this second form of rationality, the notion of ecological rationality in economics, is shared with the psychological study of fast-and-frugal heuristic decision-making:

> The term 'ecological rationality' has been used fittingly by Gigerenzer et al. (1999) for application to important discoveries captured in the concept of 'fast and frugal decision making' by individuals: 'A heuristic is ecologically rational to the degree that it is adapted to the structure of an environment.' (p. 13). My application of the term is concerned with adaptations that occur within institutions, markets, management, social, and other associations governed by informal or formal rule systems – in fact, any of these terms might be used in place of 'heuristic' and this definition works for me. (Smith 2008, p. xix)

The similarities and some specific connections between the research traditions established by Vernon Smith in economics and Gerd Gigerenzer in psychology that evolve around this shared notion of ecological rationality and lead to a functional view of heuristics are juxtaposed in Table 6.1 (for a juxtaposition of Smith's and Kahneman's approach to the theory and modeling of human behavior, see Altman 2004). Moreover, Table 6.1 provides two items under each connected notion. The first item illustrates the overlap between the two views, and the second outlines research questions that relate the particular preceding topic to the core of behavioral economics inquiry.

In the study of human action, Smith calls for supplanting the traditional constructivist framework of rationality with the ecological one. In a similar vein, Gigerenzer calls for 'a better understanding of human rationality than that relative to content-blind norms' (2008, p. 19). Constructivist rationality derives normative benchmarks from formal frameworks such as logics and probability theory, where the situation in which a choice is made is abstracted from its content. Thus, these norms are blind to the content of the decision-making situation. Regrettably, 'these were of little relevance for *Homo sapiens*, who had to adapt to a social and physical world, not to systems with artificial syntax, such as the laws of logic' (Smith 2008, p. 19). In cognitive science, the study of error has fallen prey to a major error by maintaining norms of logic and statistics, which despite their coherent and consistent elegance, and at the price of preserving this elegance, could lack meaningful association to evaluation of human decision-making behavior.[3] Pointing out that this is an unjustified extension from the study of perceptual errors to the cognitive domain, Mousavi and Gigerenzer (2011; see also Gigerenzer 1991, 1996) argue for adopting and developing content-sensitive norms for the study of human cognition and behavior. For example, when the famous Wason selection task (Wason 1966) is given content by assigning two roles of employee and employers to the players who both are tasked with cheating detection, one group's correct strategy aligns with the logical truth table associated with the conditional, but the other does not. Thus, logic appears to capture one part of the content and miss the other part. In this case, if judgment is evaluated based on logical truth, one group appears to have wrong judgment, whereas their judgment is completely correct with respect to the role (content) that they are assigned (Gigerenzer and Hug 1992). Thus, what counts as human rationality depends on the content and domain,

Table 6.2 Decisions under risk versus uncertainty

Nature of unknown	Knightian probability	Decision process	Method	Generated knowledge
Risk	A priori (design; propensity)	Deductive	Use probability theory to model the underlying structure; optimization	Deterministic knowledge (as in lotteries); e.g., objective odds
Risk	Statistical (frequencies in the long run)	Inductive (statistical inference)	Use statistical inference; optimization	Stochastic knowledge; e.g., estimates of correlations
Uncertainty	Estimate; conduct based on opinion; not fully reasoned	Heuristic	Select a heuristic that is ecologically rational for a task; exploratory data analysis	Satisficing solutions when optimizing is not feasible; intuition (as in entrepreneurship)

Source: Adapted from Mousavi and Gigerenzer (2014) with permission.

characterized, in turn, shapes and limits the type of solution that can be produced because it dictates the form of knowledge generated from the processing of information. This is illustrated in Table 6.2, wherein, in addition to deductive and inductive processes, a third heuristic process is proposed, which involves a less than exhaustive search for or consideration of information and leads to knowledge that is simply good enough for making a successful decision, but by no means exhausts information or optimizes across conditions. Note that the idea is not that these decision processes are mutually exclusive categories. Rather, the current categorization is meant to shed light on the nature of knowledge used and created in the process of decision making. For resolving disequilibrium, boundedly rational agents tend to use different types of strategies compared to fully rational agents (Simon 1955; Selten 1998). They restore the equilibrium by finding satisficing answers to their problems in situations with irreducible uncertainty, wherein exhaustive search is often unhelpful or even impossible.

Heuristic decision-making, based on good-enough reasons to act, characterizes the observed behavior primarily with respect to a functional (rather than mirror image) match between the mind of the decision maker, the particular strategy employed, and properties of the task environment. A large number of situations involving unknowns are characterized by what we refer to as fundamental uncertainty that cannot be reduced to risk calculations. This fundamental uncertainty includes what Knight refers to as an 'estimate' and extends to situations where some options, outcomes, or probabilities are fundamentally unknown (Meder et al. 2013). Heuristics are then to be viewed as less than fully reasoned strategies to deal with complexities of such uncertain unknowns by not trying to assign a probability to (including zero for ignoring) every unknown, but just forming an opinion that allows an action, what Knight calls an estimate:

> Suppose we are allowed to look into the urn containing a large number of black and red balls before making a wager, but are not allowed to count the balls: this would give rise to

> an estimate of probability in the correct sense; it is something very different from either the mere consciousness or ignorance on which we act if we know only that there are balls of both colors without any knowledge or opinion as to the numbers or the exact knowledge of real probability attained by an accurate counting of the balls. In the second place, we must admit that the actual basis of action in a large proportion of real cases is an estimate. Neither of these interpretations, however, justifies identifying probability with an estimate. . ..The exact science of inference has little place in forming the opinions upon which decisions of conduct are based, and that this is true whether the implicit logic of the case is prediction on the ground of exhaustive analysis or a probability judgment, a priori or statistical. We act upon estimates rather than inferences, upon 'judgment' or 'intuition', not reasoning, for the most part. (Knight 1921, p. 23)

Note that heuristics can be applied to a variety of situations. For instance, the priority heuristic (Brandstätter et al. 2006) provides a lexicographic strategy to choose among lotteries, the classical paradigm for decision-making under risk. The priority heuristic chooses between lotteries by comparing their probabilities and outcomes (gains or losses) lexicographically (that is, one at a time) instead of combining probabilities and gains in a weighted sum. Surprisingly, this simple model logically implies long-lasting anomalies of human choice behavior, such as the Allais paradox, the fourfold pattern of risk, and the certainty effect (Katsikopoulos and Gigerenzer 2008). Also, heuristic methods may be applied to a wide range of other problems, such as catching a ball. One way of solving the problem would be to compute the trajectory of the ball and move towards the inferred landing point, but owing to the number of causally relevant variables (for example, velocity and wind resistance) and the associated uncertainties, this is difficult to impossible. However, the problem can be tackled by a relatively simple algorithm according to which the catcher does not compute the landing point, but focuses on the ball and keeps a constant angle of elevation of gaze while running in the direction (McLeod and Dienes 1996). This example also illustrates the tight connection between heuristics and evolutionary or learned capacities. Applying the gaze heuristic requires certain capacities (that is, to fixate a moving object with your eyes, locomotion, and so on) that are necessary for using the strategy, which are far from trivial and cannot be reduced to merely computing the solution.

The simplicity of heuristics is a feature, rather than a flaw. Heuristics are successful because of their simplicity, which involves a beneficial degree of ignoring information, not despite it – something that may puzzle many economists, when trying to make sense of the observed behavior through the lens of constructivist rationality, but is practiced regularly by laypeople. Whether the benefits of heuristics come at a prohibitive cost is not a matter of opinion but should be understood as an empirical question. In the following we turn to the world of business and finance as an example of an uncertain environment in which the successful use of heuristic strategies accords with the ecological notion of rationality.

SUCCESSFUL HEURISTICS IN FINANCE AND BUSINESS DECISION-MAKING

The previous sections have provided theoretical arguments for a shift towards the norm of ecological rationality and proposed that heuristics are appropriate tools to tackle complex problems under conditions of uncertainty. Given that practitioners care more about measurable results than about abstract beauty or consistency with axioms, it is not surprising that some of the strongest examples for successful use of heuristics stem from the world of finance and business decision making.

Any form of resource allocation faces two fundamental problems: (1) how should we distribute our assets over all available options, and (2) when should we switch from one option to another? Theoretically, the asset allocation problem is solved by the Nobel prize-winning mean-variance model of Markowitz (1952), which provides the optimal investment portfolio by maximizing profit for a given level of risk. By contrast, a dominant strategy employed by many people is a simple 1/*N* heuristic that allocates resources equally across all considered assets. When contributing to retirement savings plans, 1/*N* has been called 'naive diversification' and is believed to incur substantial costs to investors (Benartzi and Thaler 2001). However, when DeMiguel et al. (2009) compared Markowitz's solution and its modern variants with 1/*N*, the heuristic performed at least as strongly as the mean-variance model. One reason for the surprising success of the simple 1/*N* heuristic lies in the so-called bias-variance dilemma (Geman et al. 1992), pertaining to minimizing the prediction error. The prediction error has two contributing components: bias and variance. The error due to bias has been at the center of behavioral economics, and has led to enlisting several debiasing techniques. The error due to variance, however, has not been receiving much attention. 1/*N* exemplifies a simple allocation mechanism, which is highly biased but has no variance, and overall generates less prediction error under certain circumstances. 1/*N* can be viewed as a special case of the Markovitz model, which implies that the flexibility of the Markowitz model comes at the potential cost of an increased estimation error (Neth et al. 2014; see Gigerenzer and Brighton 2009, for a general discussion of heuristics and the bias-variance dilemma). As the benefits of 1/*N* have been shown to generalize to investments in international stock markets and different asset classes (Jacob et al. 2013) it seems smart of Markowitz to have used 1/*N* himself, rather than his own method of portfolio optimization (Benartzi and Thaler 2001, p. 80). The 1/*N* heuristic is an instance of a more general equality rule (Messick 2008) that is also applied in parental investments (Hertwig et al. 2002).

Regarding the switching problem (that is, when and how to switch between different options), biologists and psychologists have examined simple, yet highly effective stopping rules in animal foraging theory (Green 1984; Stephens and Krebs 1986) and research on human multitasking behavior (for example, Payne et al. 2007). An applied instance of a simple and successful temporal threshold rule is the hiatus heuristic (Wübben and von Wangenheim 2008), which allows directing marketing efforts by abandoning customers who have not purchased anything for a certain amount of time, say, a number of months. This period of time that sets the threshold is called the hiatus.

Interestingly, heuristic models combine explanatory parsimony with higher predictive power for situations of uncertainty.[4] This is in direct contrast with the prevalent method used by mainstream behavioral economics of adding flexible parameters to Bernoulli utility functions in order to incorporate psychological factors of observed behavior, which in turn adds to the complexity of the model but often costs predictive power (Berg and Gigerenzer, 2010).

The abundance and ubiquity of successful heuristics in applied contexts raises the question whether existing heuristics can be used to create new or improve existing strategies.

One aspect of ecological rationality – as a research program – aims at teasing out the elements of successful strategies to adapt and refine them to novel situations. In addition, understanding how, when, and why heuristics work well can guide the design of intuitive decision systems that fit the strategies that people naturally use. For instance, highly transparent and teachable fast-and-frugal trees (Martignon et al. 2003) have been designed for coronary care unit allocations (Green and Mehr 1997), for diagnosing patients with clinical depression (Jenny et al. 2013), and for identifying vulnerable banks in financial regulation (Aikman et al. 2014; Neth et al. 2014). Thus, successful heuristics are not only discovered, but can also be specifically designed to create efficient and effective tools. Next, we demonstrate this transformative potential of ecological rationality in the context of public policy decisions and the communication of medical risks.

APPLIED LESSONS FROM THE STUDY OF ECOLOGICAL RATIONALITY

In the following, we extend our discussion of ecological rationality to applied issues. First, we critically evaluate the idea of nudging, a policy-making tool rooted in the behavioral economics approach. Subsequently, we discuss probabilistic reasoning and risk literacy as an example of how successful decision engineering can be guided by psychological research that takes the match between cognitive processes and the information structure of the environment seriously. This approach is based on the idea of making people risk literate to help them make better, more informed decisions, rather than merely nudging them towards an externally specified goal.

The Risk of Using Nudges in an Uncertain World

How to conceptualize human rationality is not only an academic issue, but has strong implications for policy making and the question of how to help people make better decisions. A prominent example is the so-called 'nudge' approach, which (in the tradition of the heuristics and biases program) assumes that people frequently make inferior decisions because their thinking is fundamentally biased and error-prone (Thaler and Sunstein 2008). The proposed remedy is to structure the choice situation so that people are more likely to make better decisions, while retaining freedom of choice (Grüne-Yanoff and Hertwig 2015). Examples include nudging people towards healthier dietary choices by arranging food items (for example, in a canteen) such that healthier items are more readily available, or setting default options in retirement saving plans in a way that people automatically enroll in higher saving contributions, unless they deliberately opt out (for an alternative approach to public policy that advocates financial literacy, see Altman 2012).

However, what are the implications of nudges in an uncertain world, where it may not always be clear what it means to make better decisions? Consider nudges in the health domain. In the past decades, several countries have set up screening programs (for example, for breast cancer and prostate cancer), with the long-term goal of reducing cancer-related mortality rates. The idea behind these programs is to detect cancer in early stages, in order to treat people earlier and more effectively (or at least more cost-efficiently). A key question is how to provide information to the target group to increase participation; one way of doing so is to resort to the nudge approach. For instance, different nudges have been used in the Danish breast cancer screening program to increase participation rates (Ploug et al. 2012; see Gøtzsche and Jørgensen 2013, for a related analysis of the British NHS breast cancer screening programme). Women in the target group received an invitation to participate, along with an information leaflet. The default was a pre-booked appointment, so that women needed to actively opt out. The leaflet also stated that after evaluating the pros and cons the Danish National Board of Health recommends participating in screening. These strategies aim at nudging people towards a goal defined by experts and policy makers, based on the assumption that it is in people's interest to participate.

It could be argued that people should be nudged to participate in screening – after all, is it not to their own benefit to participate if such a program can reduce the risk of dying from cancer (or at least lead to better treatment with less side effects)? What remains unclear, however, is whether participating in screening always serves people's interests, given that there are different benefits and costs associated. In the case of breast cancer screening, the (currently) available data show that over a period of ten years, eight out of 2000 women who do not participate in screening die from breast cancer, compared with seven out of 2000 women who do participate (Gøtzsche and Jørgensen 2011). At the same time, however, screening entails potential and harms, such as overtreatment resulting from false positive test results (for example, unnecessary removal of the breast). Also, the overall mortality rate (that is, total number of women dying from all causes) does not vary between women participating and not participating in breast cancer screening (Gøtzsche and Jørgensen 2013). Yet this crucial information was omitted from the leaflet of the Danish breast-screening program, thereby undermining the possibility to make an informed decision based on considering and evaluating the potential benefits and harms (see Gigerenzer 2014a; Gigerenzer and Edwards 2003; Gigerenzer et al. 2007).

For other screening programs, such as PSA-based screening for prostate cancer, the current evidence indicates that the potential harms actually outweigh the potential benefits. Consequently, the US Preventive Services Task Force explicitly recommends against prostate-specific antigen (PSA)-based screening for prostate cancer (Moyer 2012). This recommendation was issued after a period of uncertainty in which not enough evidence was available to determine whether PSA-based screening would be beneficial or not.

These examples highlight critical issues in the foundation and application of nudges. An important precondition for the nudge approach is the possibility to determine – from the perspective of the choice architect – which decision is in the best interest of the decision maker. It may be self-evident that an apple is a healthier choice for a snack than a chocolate bar, but in other domains, such as medical treatments, determining which choice is in the decision maker's best interest may be highly uncertain and dependent on individual preferences. A woman provided with the currently available evidence on breast cancer screening may decide that the benefits outweigh potential harms and therefore participate. However, she may also conclude that the potential harms outweigh the potential benefits and therefore decide that she would be better off by not participating. In each case, the decision will depend on how she values the associated benefits and costs. This, in turn, highlights the importance of providing people with the necessary information to make informed decisions, relative to their goals, values, and individual preferences, and not merely nudging them towards an externally specified goal. Importantly, not all information is created equal, and identifying or designing transparent and intuitive information presentation formats is crucial for both psychology and behavioral economics (see below).

In sum, the nudge approach rests on the assumption that there is one right way to make decisions, which applies to everybody, and that the choice architect knows what is in the best interest of the decision maker and can therefore enforce it. While this may well be true in some cases, we advise against an uncritical application of the approach to policy making. Nudges may be an effective tool in some circumstances, but like any tool (fast-and-frugal heuristics included), they can cut both ways and need to be handled with care. In an uncertain and changing world, nudges may lead to adverse outcomes that are not in the best interest of decision makers.

In our view, rather than precluding the possibility that people can make good decisions, the goal should be to develop means for communicating the relevant information in a way that facilitates people's understanding of it, so that they can make better, more informed decisions. From the perspective of the nudge program, educating and informing people to make them risk literate (Gigerenzer et al. 2007; Gigerenzer and Muir Gray 2011) is likely to be ineffective, because the assumption (rooted in the heuristics and biases program) is that human thinking and decision making are fundamentally flawed. This view, however, neglects recent research that demonstrates how people can be helped to make better inferences (for example, inferring posterior probabilities, such as the probability of breast cancer given a positive mammogram) by conveying the relevant information in a transparent and intuitive way, without being patronizing (Gigerenzer and Hoffrage 1995; Sedlmeier and Gigerenzer 2001; Meder and Gigerenzer 2014). Similar views have been presented in other domains. In the equilibrium analysis of financial markets, although an equilibrium state is always Pareto optimal, this optimality does not necessarily coincide with the best 'wanted' outcome for all agents. This is illustrated in phishing equilibria, where 'phools,' who do not act according to what they want or is good for them, are systematically 'phished'. Akerlof and Shiller (2015) argue that when information can be used systematically in forms that would deceive the consumers, the very structure of free markets provides opportunity for exploitation, a point overlooked by behavioral economists,

> [C]uriously, to the best of our knowledge, they [behavioral economists] have never interpreted their results in the context of Adam Smith's fundamental idea regarding the invisible hand . . . It's a major reason why just letting people be Free to Choose – which Milton and Rose Friedman, for example, consider the *sine qua non* of good public policy – leads to serious economic problems. (Akerlof and Shiller 2015, p. 6)

As we discuss next, the use of accessible and intuitive representative formats such as natural frequencies can improve decision making by enhancing their probabilistic reasoning abilities.

Moving Beyond Nudges by Making People Risk Literate

Understanding of and reasoning with probabilistic and statistical information is crucial for making good decisions. For instance, an informed decision on whether to participate in a screening program requires understanding of the relevant evidence regarding potential benefits and harms and the implications of medical test results. The nudge approach and the heuristics and biases program that provides its conceptual foundation presume that people lack this capacity. Since humans are assumed to be biased and error-prone when it comes to probabilistic thinking, the suggested remedy is to nudge people into making better decisions.

However, is nudging the only way to help people make better decisions? Also, what does the psychological literature have to say about people's capacity to reason with probabilistic and statistical information? In fact, the psychological literature to date has given very different answers to these questions. In the 1950s and 1960s, researchers began investigating experimentally whether people's inferences correspond (approximately) to probability theory in general, and to Bayes' rule in particular. For instance, Phillips and Edwards (1966) used (incentivized) bookbag and poker chip scenarios, in which they presented subjects with a sequence of draws that came from either a bag with more red than blue chips or a bag with more blue than red chips. The question of interest was whether subjects would update their beliefs regarding the bag in accordance with Bayes' rule, given the observed data. This and other studies indicated that the human mind is able to deal with probabilistic inferences, although it was frequently observed that the amount of belief revision was not as extensive as prescribed by Bayes' rule (a phenomenon referred to as conservatism; Edwards 1968). Peterson and Beach (1967) coined the term 'man as intuitive statistician,' mirroring the Enlightenment view that the laws of probability are also the laws of the mind (Daston 1988).

This view stands in stark contrast to the conclusions drawn from later research in the heuristics and biases tradition: 'In making predictions and judgments under uncertainty, people do not appear to follow the calculus of chance or the statistical theory of prediction' (Kahneman and Tversky 1973, p. 237). A key empirical finding used to corroborate this claim was that people often do not seem to appreciate base rate information (prior probabilities) when making Bayesian inferences. A prominent example is the so-called 'mammography problem' (Eddy 1982; Gigerenzer and Hoffrage 1995). Figure 6.1 (left-hand side) gives an example of the task in which the goal is to derive the posterior probability of a woman having breast cancer given a positive mammogram, based on information about the base rate (prior probability) of cancer, the probability of obtaining a positive test result for a woman having the disease, and the probability of obtaining a positive test for women without cancer. The probability tree (Figure 6.1, middle left) visualizes the given information, which consists of a set of unconditional and conditional probabilities. The posterior probability can be inferred using Bayes' rule (Figure 6.1, bottom left), according to which the probability of cancer given a positive test result is about 8 percent. Yet many people give much higher estimates in this particular scenario, which has been interpreted as neglect of the base rate. These and similar findings have led to the view that people's probabilistic reasoning is fundamentally flawed (but see Koehler 1996 for a critical review).

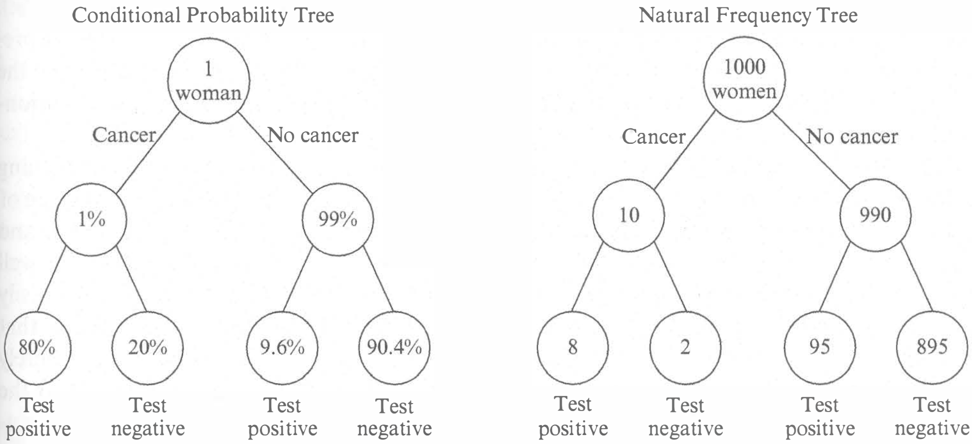
More recently, however, psychologists have begun to identify the conditions under which people are able to make sound probabilistic inferences. This is a case in point for successfully exploiting the ecological rationality of designed tools. Instead of focusing on human errors, the focus is shifted to human engineering: What can be done to help people with probabilistic reasoning? A key insight from this line of research is the power of presentation formats: The extent to which people are able to make sound probabilistic inferences crucially depends on the ways in which the relevant information is conveyed.

Task

The probability of breast cancer is 1 percent for a woman at the age of 40 who participates in routine screening. If a woman has breast cancer, the probability is 80 percent that she will get a positive mammography. If a woman does not have breast cancer, the probability is 9.6 percent that she will also get a positive mammography. A woman in this age group had a positive mammography in a routine screening. What is the probability that she actually has breast cancer? ___ percent

Ten out of every 1000 women at the age of 40 who participate in routine screening have breast cancer. Eight of every 10 women with breast cancer will get a positive mammography. Ninety-five out of every 990 women without breast cancer will also get a positive mammography. Here is a new representative sample of women at the age of 40 who got a positive mammography in routine screening. How many of these women do you expect to actually have breast cancer? ___ out of ___

Representation



Inference

$$P(\textit{cancer} \mid \textit{test positive}) = \frac{P(\textit{test positive} \mid \textit{cancer}) \times P(\textit{cancer})}{P(\textit{test positive})}$$

$$= \frac{0.8 \times 0.01}{0.08 \times 0.01 + 0.096 \times 0.99} \approx 0.08$$

$$P(\textit{cancer} \mid \textit{test positive}) = \frac{N(\textit{test positive} \cap \textit{cancer})}{N(\textit{test positive})}$$

$$= \frac{8}{(8 + 95)} \approx 0.08$$

Note: The middle panel shows two types of task representations, a conditional probability tree (left) and a natural frequency tree (right). The bottom row shows two (mathematically equivalent) ways of deriving the posterior probability of having cancer given a positive mammogram, P(cancer|test positive), either by using Bayes' rule (left) or by deriving it from the natural frequency information.

Source: Task descriptions (top row) are taken from Gigerenzer and Hoffrage (1995).

Figure 6.1 Example of a simple probabilistic reasoning task

Particular frequency formats, presented verbally or graphically, have been shown to foster people's inferences, in the laboratory and outside of it.

Consider the variant of the mammography problem shown in Figure 6.1 (top right), adapted from Gigerenzer and Hoffrage (1995). Here, instead of using conditional probabilities, information is presented in terms of natural frequencies. The key difference to conveying information in terms of conditional probabilities is that natural frequencies preserve base rate information. The natural frequency tree (Figure 6.1, middle right) illustrates this. This tree represents information as it would result from natural sampling (Kleiter 1994), providing a joint frequency distribution over the two variables (cancer and test result) that reflects the base rate of cancer in the sample (as opposed to systematic sampling, which fixes base rates a priori). Several studies have shown that presenting information this way strongly improves the accuracy of people's inferences (for a review, see Meder and Gigerenzer 2014). One reason is that the provided information makes it easier to calculate the desired quantity, namely that of 103 women who receive a positive mammogram (95 + 8), only eight actually have breast cancer (Figure 6.1, bottom right). This echoes Simon (1978; see also Larkin and Simon 1987), who noted that two representations are informationally equivalent if one representation can be translated into the other without losing information, but that this does not imply that they are computationally equivalent.

Importantly, these findings have guided the development of efficient tools and teaching methods to help people deal with statistical information. Key examples include the use of natural frequencies for understanding the implications of diagnostic tests (Hoffrage and Gigerenzer 1998; Labarge et al. 2003) and forensic evidence (Lindsey et al. 2003), as well as the use of so-called fact boxes to convey medical information in a concise and easily understandable format (Schwartz et al. 2009; Gigerenzer 2014b). Research also shows that training people to use the power of presentation formats is more sustainable than merely teaching them the application of Bayes' rule (Sedlmeier and Gigerenzer 2001). Over the past decade, different ways have been explored for the intuitive and transparent communication of health information, as well as for the development of graphical presentation formats that help people make sense of health statistics (for reviews see Akl et al. 2011; Gigerenzer et al. 2007).

The upshot is that the human mind is not necessarily doomed when it comes to probabilistic thinking. Whereas many researchers endorse the view that people inevitably fall prey to 'cognitive illusions', harnessing the power of presentation formats offers a means to help people make sound probabilistic inferences. This, in turn, can provide a foundation for helping people make better decisions without nudging them towards an externally specified goal.

CONCLUSION

A functional match between mind and the task environment leads to successful decision making. Fast-and-frugal heuristics are ecologically rational when used under conditions that satisfy such functional matches. Thus, boundedly rational agents make smart decisions by exploiting the ecological rationality of heuristics. Heuristics can capitalize on learned and evolved capacities, or can be designed to create efficient and effective tools for decision making. A heuristic is neither good nor bad per se. Rather, the effectiveness of a heuristic strategy can only be gauged with respect to the structure of information in the environment within which it is used. As such, errors can be scrutinized as informative where they are indicating a mismatch between the environment, strategies, or evolved and learned capacities. Specifying proper matches and teasing out the mismatches between heuristics and their task environment constitutes the study of ecological rationality of heuristics.

Intelligent behavior, when appearing less than neoclassically rational, can be understood by breaking free of the restrictive benchmarks imposed by constructivist rationality. The answer is to be found in the ecological rationality of intelligent behavior, because in many real-world situations it is simply not rational to be rational. Through the complementary frame of ecological rationality, intelligence can be understood to be beyond the agents' mind and without requiring complete comprehension of rules. Also, smart behavior emerges where proper evolved or learned capacities are triggered in reaction to the structure of the task environment.

This chapter primarily focused on recent theoretical developments regarding the ecological nature of humans' bounded rationality that ought to be of interest to behavioral economists. We invite economists and psychologists to join our dialogue and dig into less explored insights from psychology that promise informing behavioral economics on real-world, practical, and smart decision making. Beyond encouraging economists to adopt psychological insights into their models and theories, Simon (1959, p. 253) also challenges economists to communicate their ideas and findings to psychologists:

> the psychologist will also raise the converse question – whether there are developments in economic theory and observation that have implications for the central core of psychology . . . Influence will run both ways.

NOTES

1. Fast-and-frugal heuristics are interchangeably used in this text with simple and smart heuristics.
2. Savage (1954) drew significantly on the *Theory of Games and Economic Behavior* (von Neumann and Morgenstern 1947) and proposed a normative reading of the subjective expected utility theoretical framework.
3. McCloskey (1991) spells out the pragmatic significance of this point in 'Economic science: a search through the hyperspace of assumptions?' where she portrays the practice of axiomatic economics as a mathematical practice faithful to math departments' ideal of consistency and coherence, but incapable of grasping and providing solutions to real-world problems.
4. A series of papers (*Journal of Business Research*, vol. 67, 2014) on the effectiveness of fast-and-frugal heuristics in business decision-making demonstrate this point.

REFERENCES

Aikman, D., M. Galesic, G. Gigerenzer, S. Kapadia, K.V. Katsikopoulos, A. Kothiyal et al. (2014), 'Taking uncertainty seriously: simplicity versus complexity in financial regulation', Financial Stability Paper No. 28, May, Bank of England, London.

Akerlof, G.A. and R.J. Shiller (2015), *Phishing for Phools: The Economics of Manipulation and Deception*, Princeton, NJ: Princeton University Press.

Akl, E.A., A.D. Oxman, J. Herrin, G.E. Vist, I. Terrenato, F. Sperati et al. (2011), 'Using alternative statistical formats for presenting risks and risk reductions', *Cochrane Database of Systematic Reviews*, 16 March, CD006776, doi:10.1002/14651858.CD006776.pub2.

Altman, M. (2004), 'The Nobel Prize in behavioral and experimental economics: a contextual and critical appraisal of the contributions of Daniel Kahneman and Vernon Smith', *Review of Political Economy*, **16** (1) 3–41.

Altman, M. (2012), 'Implications of behavioural economics for financial literacy and public policy', *Journal of Socio-Economics*, **41** (5), 677–90.

Benartzi, S. and R.H. Thaler (2001), 'Naive diversification strategies in defined contribution saving plans', *American Economic Review*, **91** (1), 79–98.

Berg, N. and G. Gigerenzer (2010), 'As-if behavioral economics: neoclassical economics in disguise?', *History of Economic Ideas,* **18** (1), 133–66.

Brandstätter, E., G. Gigerenzer and R. Hertwig (2006), 'Priority heuristic: making choices without trade-offs', *Psychological Review*, **113** (2), 409–32.

Daston, L.J. (1988), *Classical Probability in the Enlightenment*, Princeton, NJ: Princeton University Press.

DeMiguel, V., L. Garlappi and R. Uppal (2009), 'Optimal versus naive diversification: how inefficient is the 1/N portfolio strategy?', *Review of Financial Studies*, **22** (5), 1915–53.

Dewey, J. (1938), 'Logic: the theory of inquiry', reprinted in J.A. Boydston (ed.) (1986), *John Dewey: The Later Works*, vol. 12, Carbondale, IL: Southern Illinois University Press.

Eddy, D.M. (1982), 'Probabilistic reasoning in clinical medicine: problems and opportunities', in D. Kahneman, P. Slovic and A. Tversky (eds), *Judgment under Uncertainty: Heuristics and Biases*, Cambridge: Cambridge University Press, pp. 249–67.

Edwards, W. (1968), 'Conservatism in human information processing', in B. Kleinmuntz (ed.), *Formal Representation of Human Judgment*, New York: Wiley, pp. 17–52.

Geman, S., E. Bienenstock and R. Doursat (1992), 'Neural networks and the bias/variance dilemma', *Neural Computation*, **4** (1), 1–58.

Gigerenzer, G. (1991), 'How to make cognitive illusions disappear: beyond "heuristics and biases"', *European Review of Social Psychology*, **2** (1), 83–115.

Gigerenzer, G. (1996), 'On narrow norms and vague heuristics: a reply to Kahneman and Tversky (1996)', *Psychological Review*, **103**(3), 592–6.

Gigerenzer, G. (2008), *Rationality for Mortals: How People Cope with Uncertainty*, New York: Oxford University Press.

Gigerenzer, G. (2014a), 'Breast cancer screening pamphlets mislead women', *BMJ*, **348** (25 April), g2636–g2636, doi:10.1136/bmj.g2636.

Gigerenzer, G. (2014b), *Risk Savvy: How to Make Good Decisions*, New York: Viking.

Gigerenzer, G. and H.J. Brighton (2009), 'Homo heuristicus: why biased minds make better inferences', *Topics in Cognitive Science*, **1** (1), 107–43, doi:10.1111/j.1756-8765.2008.01006.x.

Gigerenzer, G. and A. Edwards (2003), 'Simple tools for understanding risks: from innumeracy to insight', *BMJ*, **327** (7417), 741–4, doi:10.1136/bmj.327.7417.741.

Gigerenzer, G. and U. Hoffrage (1995), 'How to improve Bayesian reasoning without instruction: frequency formats', *Psychological Review*, **102** (4), 684–704, doi:10.1037/0033-295X.102.4.684.

Gigerenzer, G. and K. Hug (1992), 'Domain-specific reasoning: social contracts, cheating, and perspective change', *Cognition*, **43** (2), 127–71.

Gigerenzer, G. and J.A. Muir Gray (eds) (2011), *Better Doctors, Better Patients, Better Decisions: Envisioning Health Care 2020*, Cambridge, MA: MIT Press.

Gigerenzer, G., W. Gaissmaier, E. Kurz-Milcke, L.M. Schwartz and S. Woloshin (2007), 'Helping doctors and patients make sense of health statistics', *Psychological Science in the Public Interest*, **8** (2), 53–96, doi:10.1111/j.1539-6053.2008.00033.x.

Gigerenzer, G., P.M. Todd and the ABC Research Group (1999), *Simple Heuristics that Make Us Smart*, New York: Oxford University Press.

Goldman, A. (1988), *Empirical Knowledge*, Berkeley, CA: University of California Press.

Gøtzsche, P.C. and K.J. Jørgensen (2011), 'The breast screening programme and misinforming the public', *Journal of the Royal Society of Medicine*, **104** (9), 361–9, doi:10.1258/jrsm.2011.110078.

Gøtzsche, P.C. and K.J. Jørgensen (2013), 'Screening for breast cancer with mammography', *Cochrane Database of Systematic Reviews*, (6), 4 June, CD001877, doi:10.1002/14651858.CD001877.pub5.

Green, R.F. (1984), 'Stopping rules for optimal foragers', *American Naturalist*, **123** (1), 30–43.

Green, L. and D.R. Mehr (1997), 'What alters physicians' decisions to admit to the coronary care unit?', *Journal of Family Practice*, **45** (3), 219–26.

Grüne-Yanoff, T. and R. Hertwig (2015), 'Nudge versus boost: how coherent are policy and theory?', *Minds and Machines*, **25** (1–2), 1–35, doi:10.1007/s11023-015-9367-9.

Hertwig, R., J.N. Davis and F.J. Sulloway (2002), 'Parental investment: how an equity motive can produce inequality', *Psychological Bulletin*, **128** (5), 728–45.
Hoffrage, U. and G. Gigerenzer (1998), 'Using natural frequencies to improve diagnostic inferences', *Academic Medicine: Journal of the Association of American Medical Colleges*, **73** (5), 538–40.
Jacobs, H., S. Müller and M. Weber (2013), 'How should individual investors diversify? An empirical evaluation of alternative asset allocation policies', *Journal of Financial Markets*, **19** (June), 62–85.
Jenny, M.A., T. Pachur, S. Lloyd Williams, E. Becker and J. Margraf (2013), 'Simple rules for detecting depression', *Journal of Applied Research in Memory and Cognition*, **2** (3), 149–57.
Kahneman, D. and A. Tversky (1973), 'On the psychology of prediction', *Psychological Review*, **80** (4), 237–51, doi:10.1037/h0034747.
Kahneman, D., P. Slovic and A. Tversky (eds) (1982), *Judgment under Uncertainty: Heuristics and Biases*, Cambridge: Cambridge University Press.
Katsikopoulos, K.V. and G. Gigerenzer (2008), 'One-reason decision-making: modeling violations of expected utility theory', *Journal of Risk and Uncertainty*, **37** (1), 35–56, doi:10.1007/s11166-008-9042-0.
Kleiter, G.D. (1994), 'Natural sampling: rationality without base rates', in *Contributions to Mathematical Psychology, Psychometrics, and Methodology*, New York: Springer, pp. 375–88.
Knight, F.H. (1921), *Risk, Uncertainty and Profit*, New York: Hart, Schaffner and Marx.
Koehler, J.J. (1996), 'The base rate fallacy reconsidered: descriptive, normative and methodological challenges', *Behavioral and Brain Sciences*, **19** (1), 1–54.
Labarge, A.S., R.J. McCaffrey and T.A. Brown (2003), 'Neuropsychologists' abilities to determine the predictive value of diagnostic tests', *Archives of Clinical Neuropsychology: The Official Journal of the National Academy of Neuropsychologists*, **18** (2), 165–75.
Larkin, J.H. and H.A. Simon (1987), 'Why a diagram is (sometimes) worth ten thousand words', *Cognitive Science*, **11** (1), 65-100, doi:10.1111/j.1551-6708.1987.tb00863.x.
Lindsey, S., R. Hertwig and G. Gigerenzer (2003), 'Communicating statistical DNA evidence', *Jurimetrics*, **43** (2), 147–63.
Markowitz, H.M. (1952), 'Portfolio selection', *Journal of Finance*, **7** (1), 77–91.
Martignon, L., O. Vitouch, M. Takezawa and M.R. Forster (2003), 'Naïve and yet enlightened: from natural frequencies to fast and frugal decision trees', in D. Hardman and L. Macchi (eds), *Thinking: Psychological Perspectives on Reasoning, Judgment and Decision Making*, Chichester: John Wiley & Sons, pp. 189–211.
McCloskey, D. (1991), 'Economic science: a search through the hyperspace of assumptions?', *Methodus*, **3** (1), 6–16.
McLeod, P. and Z. Dienes (1996), 'Do fielders know where to go to catch the ball, or only how to get there?', *Journal of Experimental Psychology: Human Perception and Performance*, **22** (3), 531–43, doi:10.1037/0096-1523.22.3.531.
Meder, B. and G. Gigerenzer (2014), 'Statistical thinking: no one left behind', in E.J. Chernoff and B. Sriraman (eds), *Probabilistic Thinking*, Dordrecht: Springer, pp. 127–48.
Meder, B., F. Le Lec and M. Osman (2013), 'Decision making in uncertain times: what can cognitive and decision sciences say about or learn from economic crises?', *Trends in Cognitive Sciences*, **17** (6), 257–60, doi.org/10.1016/j.tics.2013.04.008.
Messick, D.M. (2008), 'Equality as a decision heuristic', in B.A. Mellers and J. Baron (eds), *Psychological Perspectives on Justice: Theory and Applications*, Cambridge, MA: Cambridge University Press, pp. 11–31.
Mousavi, S. and G. Gigerenzer (2011), 'Revisiting the "error" in studies of cognitive errors', in D.A. Hofmann and M. Frese (eds), *Errors in Organizations*, New York: Routledge, pp. 97–112.
Mousavi, S. and G. Gigerenzer (2014), 'Risk, uncertainty, and heuristics', *Journal of Business Research*, **67** (8), 1671–8.
Mousavi, S. and R. Kheirandish (2014), 'Behind and beyond a shared definition of ecological rationality: a functional view of heuristics', *Journal of Business Research*, **67** (8), 1780–85.
Moyer, V.A. (2012), 'Screening for prostate cancer: U.S. Preventive Services Task Force recommendation statement', *Annals of Internal Medicine*, **157** (2), 120–34, doi:10.7326/0003-4819-157-2-201207170-00459.
Neth, H. and G. Gigerenzer (2015), 'Heuristics: tools for an uncertain world', in R. Scott and S. Kosslyn (eds), *Emerging Trends in the Social and Behavioral Sciences: An Interdisciplinary, Searchable, and Linkable Resource*, New York: Wiley. pp. 1–18.
Neth, H., B. Meder, A. Kothiyal and G. Gigerenzer (2014), 'Homo heuristicus in the financial world: from risk management to managing uncertainty', *Journal of Risk Management in Financial Institutions*, **7** (2), 134–44.
Payne, S., G. Duggan and H. Neth (2007), 'Discretionary task interleaving: heuristics for time allocation in cognitive foraging', *Journal of Experimental Psychology: General*, **136** (3), 370–80.
Peterson, C.R. and L.R. Beach (1967), 'Man as an intuitive statistician', *Psychological Bulletin*, **68** (1), 29–46.
Phillips, L.D. and W. Edwards (1966), 'Conservatism in a simple probability inference task', *Journal of Experimental Psychology*, **72** (3), 346–54.

Ploug, T., S. Holm and J. Brodersen (2012), 'To nudge or not to nudge: cancer screening programmes and the limits of libertarian paternalism', *Journal of Community Health*, **66** (12), 1193–6.
Savage, L.J. (1954), *The Foundations of Statistics*, 2nd edn, New York: Dover.
Schwartz, L.M., S. Woloshin and H.G. Welch (2009), 'Using a drug facts box to communicate drug benefits and harms: two randomized trials', *Annals of Internal Medicine*, **150** (8), 516–27.
Sedlmeier, P. and G. Gigerenzer (2001), 'Teaching Bayesian reasoning in less than two hours', *Journal of Experimental Psychology: General*, **130** (3), 380–400.
Selten, R. (1998), 'Aspiration adaptation theory', *Journal of Mathematical Psychology*, **42** (2), 191–214.
Simon, H.A. (1955), 'A behavioral model of rational choice', *Quarterly Journal of Economics*, **69** (1), 99–118.
Simon, H.A. (1959), 'Theories of decision-making in economics and behavioral science', *American Economic Review*, **49** (3), 253–83.
Simon, H.A. (1978), 'On the forms of mental representation', in C.W. Savage (ed.), *Perception and Cognition. Issues in the Foundations of Psychology*, vol. 9, Minneapolis, MN: University of Minnesota Press, pp. 3–18.
Smith, V.L. (2002), 'Constructivist and ecological rationality in economics', accessed 20 February 2015, at http://www.nobelprize.org/nobel_prizes/economic-sciences/laureates/2002/smith-lecture.html.
Smith, V.L. (2008), *Rationality in Economics: Constructivist and Ecological Forms*, New York: Cambridge University Press.
Stephens, D.W. and J.R. Krebs (1986), *Foraging Theory*, Princeton, NJ: Princeton University Press.
Thaler, R.H. and C.R. Sunstein (2008), *Nudge: Improving Decisions about Health, Wealth, and Happiness*, New Haven, CT: Yale University Press.
Tversky, A. and D. Kahneman (1974), 'Judgment under uncertainty: heuristics and biases', *Science*, **185** (4157), 1124–31.
Von Neumann, J. and O. Morgenstern (1947), *Theory of Games and Economic Behavior*, 2nd edn, Princeton, NJ: Princeton University Press.
Wason, P.C. (1966), 'Reasoning', in B.M. Foss (ed.), *New Horizons in Psychology*, vol. 1, Harmondsworth: Penguin Books.
Wübben, M. and F. von Wangenheim (2008), 'Instant customer base analysis: managerial heuristics often "get it right"', *Journal of Marketing*, **72** (3), 82–93.