To appear in the *Journal of Risk Management in Financial Institutions*
Special issue on *Behavioural Finance and Regulation*: 2014, Vol. 7 (2), pp. 134–144

Homo Heuristicus in the Financial World: From Risk Management to Managing Uncertainty

Hansjörg Neth, Björn Meder, Amit Kothiyal, Gerd Gigerenzer
Center for Adaptive Behavior and Cognition (ABC)
Max Planck Institute for Human Development
Berlin, Germany

[Final draft: Dec. 18, 2013]

What—if anything—can psychology and decision science contribute to risk management in financial institutions? The turmoils of recent economic crises undermine the assumptions of classical economic models and threaten to dethrone *Homo oeconomicus*, who aims to make decisions by weighing and integrating all available information. But rather than aiming to replace the rational actor model with irrational, biased, and fundamentally flawed agents, we advocate the alternative notion of *Homo heuristicus*, who uses simple, but ecologically rational strategies to make sound and robust decisions. Based on the conceptual distinction between risky and uncertain environments we present theoretical and empirical evidence that boundedly rational agents prefer simple heuristics over more flexible models. We provide examples of successful heuristics, explain when and why heuristics work well, and illustrate these insights with a fast and frugal decision tree that helps to identify fragile banks. We conclude that all members of the financial community will benefit from simpler and more transparent products and regulations.

Keywords: Simple heuristics, risk vs. uncertainty, ecological rationality, bias-variance dilemma, fast and frugal decision tree.

Only when you look at an ant through a magnifying glass on a sunny day you realise how often they burst into flames.
(Harry Hill)

Science has a notorious tendency to create the phenomena it studies. But deceptive interactions between methods and results loom just as large in other domains. Specifically, the rules and regulations that govern our financial system tend to become an integral part of it, so that misguided regulatory efforts risk fanning the flames of future financial disasters.

In this paper, we question the common belief that complex problems automatically call for complex solutions. As an alternative, we suggest that simple, yet robust strategies provide important insights and offer potential solutions for managing financial systems under uncertainty. To develop our case, we first examine the nature of financial systems and distinguish situations of risk from situations of uncertainty. If financial systems are fundamentally uncertain, theoretical and empirical results from psychology and decision science suggest that simple heuristics may provide more accurate and robust predictions than more flexible models. We present examples of successful heuristics and explain the conditions under which they tend to work well. To show how simple heuristics can facilitate financial regulation we illustrate a fast and frugal decision tree that helps to identify fragile banks. In the concluding section, we sketch additional means and measures that should be considered when designing effective decision environments, profitable financial products, and sound regulations. As all members of the financial community stand to benefit from more transparent regulations, we trust that the virtues of simplicity will transcend and transform our current financial system.

Risk vs. Uncertainty in the Financial World

Five years after the largest financial crisis since the Great Depression economists still disagree about its causes and enabling conditions. But regardless of whether we blame excessive market deregulation, aggressive sales of subprime mortgages, speculative bubbles, or the misbehavior of selfish individuals resulting from wrong incentive structures, it is safe to say that the events that extinguished an horrendous amount of the assets invested in the Dow Jones between October 2007 and March 2009 were not just streaks of very bad luck. Instead, the financial meltdown in the U.S. and its ongoing repercussions around the world highlight two basic facts: (a) There was something wrong with the models

We thank Mirta Galesic, Konstantinos Katsikopoulos, and an anonymous reviewer for helpful feedback and suggestions. BM was supported by grant Me 3717/2 from the Deutsche Forschungsgemeinschaft (DFG) as part of the priority program *New Frameworks of Rationality* (SPP 1516). Please send correspondence to Hansjörg Neth, Center for Adaptive Behavior and Cognition, Max Planck Institute for Human Development, Email: `neth@mpib-berlin.mpg.de`.

used by the players in the financial markets, and (b) there was something wrong with the regulations that tried to prevent such devastating crises.

These acknowledgements raise several questions: First, what was wrong with the models used by the players in the financial markets? The simple answer is that they failed to predict what happened. Anyone able to anticipate the events that unfolded and culminated in the collapse of Lehman Brothers in September 2008 could have made a fortune on the basis of this forecast. But instead of making a profit by betting on an imminent downturn, most analysts and institutions incurred traumatic losses. Suddenly, handsomely paid financial experts seemed no more persuasive than sports pundits, who can endlessly recite statistics and provide retrospective rationalizations, but are utterly unable to predict the outcome of the next game.

Second, what was wrong with our regulations so that the warning systems failed to raise red flags? Financial and economic crises have occurred before (Reinhart & Rogoff, 2009), and one response to these earlier crises was to develop regulatory recommendations for banks (e.g., the Basel Accords) to detect weak links and prevent looming crises. Given the system's failure to prevent the most recent crisis, existing guidelines are currently being revised (e.g., Basel III) and new regulatory instruments are being developed and employed. For instance, so-called 'stress tests' aim to detect financial institutions' capacity to cope with potential losses resulting from adverse market events. Here, the models' purpose lies in identifying fragile banks and anticipating developments that may destabilize the system as a whole.

Prediction is notoriously difficult and the models of both regulators and investors can fail for many different reasons. A factor frequently mentioned in the context of the crisis is the immense complexity of financial systems (e.g., Mandelbrot & Hudson, 2004), which can include dynamic feedback loops and exhibit chaotic tendencies that exacerbate minute variations in initial conditions. The interactive and reflexive nature of financial markets distinguishes them from complex and dynamic systems like the weather, which behave mostly independent of the models we use to make predictions about their future states.

But without denying or diminishing the complexity of financial systems, a substantial part of the problem lies not in their circular and possibly chaotic nature, but in the type of models used to generate predictions. Perhaps the abysmal track record of financial models—especially when comparing them to the forecasts within natural sciences (Makridakis & Taleb, 2009)—stems from a mismatch between the domain of finance and the methods used to manage it (Lo & Mueller, 2010)? The call for better and more appropriate models has motivated analysts to endow existing models with presumably more realistic assumptions (Mandelbrot & Hudson, 2004) and incorporate non-normal distributions that can capture the occurrence of rare but highly consequential events (so-called *black swans*, Taleb, 2010). Similarly, the realization that cognition, emotion and motivation play an important role in financial decision-making spawned a new field of behavioral economics (Camerer, Loewenstein, & Rabin, 2004) and led to suggestions regarding the inclusion of psychological variables into economic models (like the "animal spirits" by Akerlof & Shiller, 2010). Although some of these efforts may only fill old wine into new bottles (see Berg & Gigerenzer, 2010, for a critical review) it is true that all economic decisions contain a modicum of psychology.

To examine the psychological aspects of financial decisions, consider the following examples: Private and professional investors buy or sell stocks on the basis of expectations about a company's future profitability; consumers withdraw their savings prior to an impending bank run based on beliefs about the likelihood of the bank's default and the hypothesized behavior of other customers; banks provide loans to customers on the basis of estimated risks; and politicians decide to bail out banks or countries based on assumptions about potential consequences of such actions for the financial system as a whole. An established way to model such decisions is to associate possible states of the world with values and probabilities and combine those to derive the expected value or utility of all available actions (Von Neumann & Morgenstern, 1944; Savage, 1954). The foundations of classical economics, finance and decision theory are built upon the abstract view of human beings as *Homo oeconomicus*, who acts rationally and maximizes some measure of utility by optimally weighing and integrating all relevant information.

But where do the required probabilities come from? This question leads us back to the seminal work of the economist Frank Knight, who broadly distinguished between two conceptually distinct types of decision scenarios: situations of risk vs. situations of uncertainty (Knight, 1921). Knight argued that a situation of *risk* is characterized by the existence of an objective basis to derive outcome probabilities. For instance, the chances of winning a game of chance in a casino can be calculated by applying probability theory to the rules of the game (e.g., computing the probability of a winning hand in Black Jack). Even if the details of the data generating mechanism are unknown, probabilities can sometimes still be inferred from empirical data and past experience (e.g., by analyzing a client's credit history). Knight contrasted these scenarios with conditions in which outcome probabilities are not logically deducible and cannot be directly inferred from data — a class of situations he referred to as decision making under *uncertainty*.

Arguably, all of the above scenarios of financial decision making involve substantial amounts of uncertainty. This implies that much or most of the financial world is not a casino in which *Homo oeconomicus* can place bets on the basis of well-defined risks but includes elements that remain irreducibly uncertain. Whereas Knight's original distinction was dichotomous and qualitative, most real-world situations are embedded in wider contexts and lie somewhere in-between. Thus, Knight's categories of risk vs. uncertainty constitute the extremes of a continuum of varying degrees of uncertainty (see Meder, Le Lec, & Osman, 2013, for different types of uncertainty). Important factors that determine the degree of uncertainty and the extent to which we can make accurate predictions are the available amount of relevant data, the type of model considered, and the structure of the decision environment. (See Sims, Neth, Jacobs, & Gray, 2013, for an experimental decision environment in which presumably irrational choice behavior turns out to be rational when all three factors are taken into account.)

How can we bridge the gap between economic theory and the psychological reality of decision making under uncertainty? Instead of developing economic models that can deal with uncertainty (rather than trying to reduce it to risk), psychological theories (e.g., *prospect theory*, Kahneman & Tversky, 1979) enriched economic models with free psychological parameters to model the perception of probabilities and values. People's apparent deviations from presumably normative standards (like the axioms of probability theory) have prompted researchers to abandon the ideal of *Homo oeconomicus* and describe people as relying on heuristics and biases, and prone to suffer from systematic errors and cognitive illusions (Tversky & Kahneman, 1974; Gilovich, Griffin, & Kahneman, 2002).

In our research, we pursue a different approach. Instead of fighting complexity in the world with an ever-increasing complexity in our models we explore the potential of simple strategies to solve complex problems. Rather than viewing people as pathologically biased and fundamentally flawed, we suggest that fast and frugal heuristics—simple rules that ignore information and exploit, rather than aim to avoid environmental uncertainty—hold great promise for making financial decisions. The next section introduces examples of successful heuristics and explains when and why they work well.

How People and Models Manage Uncertainty

How do organisms—animals and people alike—make predictions and decisions under uncertainty? Given the complexity of many real-world situations and agents' limited computational resources (e.g., of time and memory capacity) evolution selected strategies that work well under uncertainty. Nature successfully bets on *heuristics*—simple rules-of-thumb that can yield effective and efficient results by ignoring irrelevant information—in many different species and task domains. For instance, when bumblebees forage for food, monitoring the number of empty flowers encountered reliably signals when it is time to abandon a patch (Goulson, 2000, as cited in Hutchinson & Gigerenzer, 2005). A giving-up rule that uses a temporal threshold to trigger the decision for departure approximates the mathematical optimum (Green, 1984). Similar rules appear to govern the switching behavior of humans between multiple tasks (Payne, Duggan, & Neth, 2007). When searching for a mate, peahens refrain from examining the features of all peacocks, but only inspect a few candidates before choosing the one with the highest number of eyespots (Petrie & Halliday, 1994). Simulation studies on competitive mate search show that a simple strategy that maximizes the speed of finding a partner tends to outperform more demanding strategies that risk wasting precious time (Neth, Schächtele, Duwal, & Todd, 2011).

In psychology, there is much evidence that humans routinely use heuristics to draw inferences and make decisions (Gigerenzer, Todd, & the ABC Research Group, 1999). For instance, when inferring which of two options has a higher value on some criterion people often choose a recognized option over an unrecognized one (Goldstein & Gigerenzer, 2002). Despite its apparent naïveté, the recognition heuristic has successfully been used to predict the outcomes of tennis tournaments (Serwe & Frings, 2006) and political elections (Gaissmaier & Marewski, 2011). Similarly, simple lexicographic heuristics like *take-the-best*, that inspects cues sequentially in order of their relevance and makes a decision on the basis of the first differentiating cue, often achieve a higher predictive accuracy than more complex strategies (Gigerenzer et al., 1999; Goldstein & Gigerenzer, 2002). Many other heuristics have been identified (see Gigerenzer, Hertwig, & Pachur, 2011, for an overview) and form such an integral part of human nature that our species has been characterized as *Homo heuristicus* (Gigerenzer & Brighton, 2009).

Interestingly, the heuristics studied in biology and psychology can be applied to tackle practical problems. To predict customer relationships and target marketing efforts, Wübben and von Wangenheim (Wübben & von Wangenheim, 2008) used a simple giving-up time rule (in the spirit of Green, 1984). When aiming to identify loyal customers (e.g., of an airline or apparel store), a simple *hiatus heuristic* outperformed computationally more demanding Pareto/NBD models from the marketing literature: *If a customer has not purchased within a number of m months, he or she is no longer a customer.* The value of m is dependent on the industry in question and can be inferred from data or the intuitions of experienced managers. In the financial domain, Ortmann and colleagues (Ortmann, Gigerenzer, Borges, & Goldstein, 2008) employed the recognition heuristic to assemble profitable investment portfolios on the basis of laypeople's name recognition of public companies (but see Andersson & Rakow, 2007).

The a priori skepticism of the *heuristics and biases* program (Tversky & Kahneman, 1974; Kahneman, 2011) contrasts sharply with the ecological analysis of the *simple heuristics* perspective (Gigerenzer et al., 1999; Todd, Gigerenzer, & the ABC Research Group, 2012). This opposition presents us with a puzzle: How can heuristics both be blamed for being biased and error-prone and be praised for yielding efficient and effective solutions? On one side, heuristics are limited and provide no general-purpose strategies that can be applied to all problems and under all circumstances, but are task-specific tools adapted to particular environments. Heuristics generally offer no guarantees for arriving at correct or optimal solutions, but aim for good outcomes within reasonable time. A key difference between optimization attempts and an heuristic approach is their hunger for data and deliberation: Whereas *Homo oeconomicus* greedily uses all available information and pays no costs for extensive computation, *Homo heuristicus* exhibits *bounded rationality* (Simon, 1956) by embracing the benefits of satisfactory solutions and avoiding the excessive demands of optimal ones.

To understand the positive potential of heuristics and to identify the conditions under which they work well we need to consider the interplay between a particular strategy (a model) and the structure of the environment (the task characteristics). Heuristics generally tend to be successful if the conditions of *ecological rationality* are met, that is, if there exists a match between a particular strategy, the environment in which it is applied, and the abilities and skills of the organism applying it (Todd et al., 2012). Importantly, strategies do not need to be complex in order to succeed in a complex environment. In fact, simple strategies can yield more robust results in an uncertain world.

To illustrate this idea, consider the problem of how to assemble an investment portfolio and maximize its returns by making predictions about future asset behavior. Theoretically, the Nobel-prize winning *mean-variance model* of Markowitz (Markowitz, 1952) has solved this problem by maximizing profit for a given level of risk (operationalized as the variance of the returns of the portfolio). However, when DeMiguel and colleagues (DeMiguel, Garlappi, & Uppal, 2009) compared this model and its modern variants with a simple 1/*N* heuristic that allocates resources equally across all considered assets the mean-variance model failed to outperform the seemingly naïve 1/*N* strategy. As the surprising success of the 1/*N* heuristic generalizes to diversifications in international stock markets and over different asset classes (Jacobs, Müller, & Weber, 2013) it seems smart that Markowitz himself used this simple strategy instead of his own method of portfolio optimization (p. 80 Benartzi & Thaler, 2001).

How can the simple 1/*N* heuristic perform on par with the complex and mathematically sophisticated mean-variance portfolio? The relevant characteristics of different types of models can be analyzed in terms of the *bias-variance dilemma* (Geman, Bienenstock, & Doursat, 1992), which decomposes a model's expected prediction error into two parts (ignoring noise, such as measurement error, for simplicity):

$$prediction\ error = (bias)^2 + variance$$

In this sum, the *bias* component describes the average accuracy of an algorithm's predictions, and the *variance* component describes the variation in a model's predictions given different samples. Here, the term *bias* is given a precise mathematical definition in the context of statistics and machine learning. This notion differs from its use in the psychological literature, where it typically denotes an observed deviation from a supposedly normative model. In general, a more flexible model (e.g., a model with more free parameters) has a lower bias and higher variance. Whereas a model with high bias will tend to underfit the data (i.e., miss existing patterns), a model with high variance will typically overfit it (i.e., fit even the noise in the data). Consequentially, a good model needs to balance bias and variance in order to achieve high predictive accuracy.

Consider the portfolio selection problem given N assets. The mean-variance model of Markowitz assigns a weight to every asset, which determines the share of the asset in the portfolio and can be negative if short-selling is allowed. To calculate these weights, the model requires estimating the mean and variance of all assets considered on the basis of their past behavior, as well as their covariances. For N assets, a total of $(N^2 + 3N)/2$ parameters need to be estimated (i.e., 65 parameters for 10 assets, 5,150 parameters for 100 assets, etc.). The 1/*N* heuristic ignores all historic information and assigns a fixed weight of 1/*N* to every asset. Thus, the heuristic exhibits a high bias and zero variance. By contrast, the Markowitz model is highly flexible and includes the 1/*N* heuristic as a special case. This flexibility reduces model bias but at the cost of increasing the variance. When data is sparse, the variance term dominates the bias term. If we had a large amount of data about the past performance of assets available, then the Markowitz model would fare better. In practice, however, only a small proportion of the available data may actually be *relevant* to the current economic conditions. The non-stationarity of financial markets and the fact that structural breaks are difficult to detect impose strong limits on the availability of relevant data. Thus, even when large amounts of historic data are available, the most recent performance of assets may matter most for predicting their future performance.

To sum up: Situations with high levels of uncertainty, a large number of alternative options, and small amounts of relevant data tend to favor simple models over more flexible ones (Gigerenzer & Brighton, 2009). Whenever we are concerned with predictive accuracy—which we usually are when designing models and devising regulations—simple heuristics can outperform more flexible models by yielding robust results under uncertainty. We now show how this insight can be applied to financial regulation by presenting a heuristic decision tree designed to identify fragile banks.

Financial Regulation with Fast and Frugal Trees

An important aspect of financial regulation is to evaluate the stability of financial institutions, with the long-term goal of ensuring the stability of the financial system. Thus, regulators face a prediction problem: They have to decide whether a bank is at risk of failing based on different cues such as a banks' leverage ratio, loan-to-deposit ratio, wholesale funding ratio, etc. Once a set of relevant cues is identified, a tool (e.g., a statistical model) is required to assess the health of different banks based on the values of these cues.

A critical question is what kind of model should be used to make such inferences. Formally, the task can be conceptualized as a prediction or classification problem, for which a variety of models have been developed in statistics, machine learning, and cognitive science. Regression models are frequently being used to tackle this problem (e.g., Estrella, 2004; Ratnovski & Huang, 2009; Vazquez & Federico, 2012). These models integrate the considered cues—typically in a linear-additive fashion—and estimate their weights from the available data. The output of such models is some quantitative estimate (e.g., a probability of default for a given bank) that is supposed to help regulators and policy makers to take action.

Inspired by empirical evidence of successful heuristics and the theoretical insight that simple models—by decreasing variance and avoiding over-fitting—may achieve high predictive accuracy we suggest that simple approaches should be considered for banking regulation as well. An applicable model type are so-called *fast and frugal trees* (FFTs), that enable efficient and effective binary classification decisions by sequentially inspecting a list of diagnostic cues (Martignon, Vitouch, Takezawa, & Forster, 2003). FFTs differ from richer classification trees (Breiman, Friedman, Olshen, & Stone, 1984) in adhering to the restriction that each node has only two child nodes, of which at least one must be an exit (classification) node. In other words, whereas a standard classification tree might consider all cues and fully traverse the graph before making a classification decision, a FFT allows making a decision at every level of the tree. Thus, unlike traditional classification techniques (e.g., logistic regression) FFTs do not consider and weigh all pieces of information. Instead, search is sequential and each cue is considered in isolation. Only if the currently inspected cue does not warrant making a decision, further information is taken into account.

From a psychological perspective, the advantage of this simple decision strategy is that it allows for making fast decisions with little cognitive load. A number of studies provide empirical support that people rely on this type of simple heuristic when making decisions under uncertainty in various domains, such as medical and legal decision making (e.g., Green & Mehr, 1997; Fischer et al., 2002; Dhami, 2003). Theoretical analyses and simulations studies have been conducted to evaluate FFTs' behavior (Martignon, Katsikopoulos, & Woike, 2008) and link them with the theoretical framework for diagnostic classification decisions provided by signal detection theory (Luan, Schooler, & Gigerenzer, 2011).

Figure 1 illustrates a possible FFT for identifying high-risk banks. The tree contains three cues: leverage ratio, loan-to-deposit ratio, and wholesale funding ratio. The leverage ratio is the total amount of assets of a bank per unit of capital available to withstand losses. The loan-to-deposit ratio compares a bank's funding with its relatively illiquid assets. It regards loans as illiquid and compares these to retail deposits. The wholesale funding ratio computes the ratio of deposits provided by other financial institutions or capital markets to the total amount of deposits, including retail deposits.

The first cue considered by the model is the leverage ratio of a bank. If this exceeds a threshold ratio of 25:1 the bank is immediately classified as falling into the high-risk category. Note that this decision is made without inspecting any other cue. Only if the leverage ratio is below the threshold the second cue is evaluated. If the bank's loan-to-deposit ratio falls below 1.5:1, the bank is classified as low-risk, otherwise the third cue (wholesale-funding ratio) is inspected. Depending on the value of this last cue (and a threshold of 0.5:1) a classification decision is made. The numeric threshold values in Figure 1 are from Aikman and colleagues (Aikman et al., under review), but the tree shown here is for illustration purposes only and will not be accurate for every type of bank.

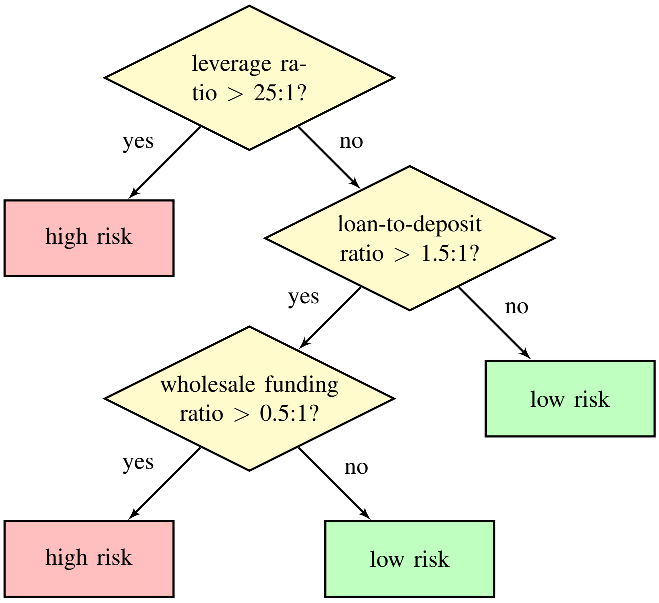

Figure 1. Example of a fast and frugal tree (FFT) to determine the risk of bank failure. (Threshold values are merely illustrative.)

There are several reasons why FFTs may provide good and predictive models for bank regulation. First, the bias-variance dilemma implies that in the presence of sparse relevant data the prediction error of a simple FFT might be lower than that of a more flexible model. Second, the tree representation is easy to understand, communicate and apply, so that the entire design and decision process on the basis of a FFT is rendered transparent.

Different methods can be used to develop FFTs (e.g., for determining included cues, their search order, and the exit structure). If expert knowledge is available, it can be used to construct a FFT, with the simplicity of the model allowing for a transparent communication process in the development phase. Alternatively (and complementary) various algorithms can be used to build FFTs based on statistical principles (Martignon et al., 2008) and to take into account different types of prediction errors (Luan et al., 2011). Any classifier can make two types of errors: Classify a high-risk bank as falling into the low-risk category (miss), and misclassify a low-risk bank as being fragile (false alarm). Different cue orders and exit structures give rise to different relative error rates. For instance, if the goal is to be careful and identify as many high-risk banks as possible, the FFT's exit structure can incorporate a more liberal decision strategy (i.e., increase the likelihood of classifying a bank as a high-risk case) at the risk of increasing the number of false alarms.

When evaluating the predictive accuracy of FFTs and other models via computer simulations under different conditions (such as the influence of varying sizes of training data on classifying novel instances) their performance is comparable to that of complex models (e.g., logistic regression techniques, Aikman et al., under review). Consequently, simple models can provide helpful tools for effective and transparent bank regulation. Past research indicates that heuristics become more applicable as unpredictability increases (e.g., in investment banking), when a larger number of parameters is involved (larger institutions), and with decreasing sample size (scarcity of relevant data).

Means and Measures for Managing Financial Uncertainty

We began this paper by emphasizing the dangers of ineffective regulations that—when being absorbed and circumvented by a reflexive financial system—can further increase the system's complexity and render the task of its regulators even more daunting. Based on theoretical and empirical evidence from psychology and decision science we suggested that—in uncertain environments and with sparse amounts of relevant data—simple heuristics often provide more accurate and robust predictions than more flexible models.

In a much-noted speech, Andrew Haldane (executive director for financial stability at the Bank of England, see Haldane & Madouros, 2012) likened the potential of simple heuristics to tackle complex problems to the image of a dog catching a frisbee by using a simple gaze heuristic (cf. McLeod & Dienes, 1996). When applied to the domain of financial regulation, the lessons learned from the fields of psychology, cognitive science and decision making imply that complex problems call for simple regulations. The previous section illustrated this idea with a FFT that could be used to identify fragile banks. Whereas this FFT is simple and transparent, its development and the cues it contains can be based on complex constructs and calculations. Thus, the space for predictive models allows for a variety of hybrid approaches, rather than being confined to a strict dichotomy of simple versus complex models.

A potential caveat against the use of simple heuristics in regulatory contexts is the fact that regulated entities may be actively seeking to circumvent some rules, whereas frisbees are typically not attempting to arbitrage the dog that is trying to catch them. Yet rather than advising against the use of heuristics, simplicity and transparency may yield additional benefits in competitive and antagonistic contexts. For instance, complex regulations tend to allow for a multitude of special cases and exceptions whereas a precisely specified simple model promises to constrain the space for regulatory arbitrage. Thus, it may actually be harder to arbitrage a simple rule than a more flexible one. Similarly, we suppose that violations of simple rules may be easier to detect and penalize than the elaborated circumventions of a complex regulatory framework. In the absence of simple rules for financial regulation such hypotheses must remain speculative, but the empirical evidence accumulated so far indicates that complex regulations have failed to avoid financial disasters.

A secondary virtue of our emphasis on simple models is to highlight the importance of choosing the right measures. For instance, when steering a complex system, not just any simple cue will suffice. In fact, using the outcome measure on which a system's performance is evaluated (e.g., annual profit) to monitor its day-to-day development could actually be a bad choice (see the distinction between control feedback and outcome feedback by Neth, Khemlani, & Gray, 2008).

Beyond the design of simple decision trees, the framework of ecological rationality allows for additional means for managing financial uncertainty. Instead of merely searching for simple strategies with high predictive accuracy the approach of *intuitive design* also focuses on shaping the structure of the physical and social environments in which all financial behavior is embedded (Todd et al., 2012; Hertwig, Hoffrage, & the ABC Research Group, 2013). For instance, basic psychological insights can inform the design of more collaborative environments and create incentive structures that align the interests of analysts and investors (cf. the *skin-in-the-game* heuristic by Taleb & Sandis, 2014). Since shaping the environment to facilitate good choices can be as effective as changing people's goals and strategies, we prefer not to patronize people. Rather than nudging people into desirable behaviors (Thaler & Sunstein, 2008) we embrace the ideal of enlightenment by rendering people more risk-literate (Gigerenzer, 2002, 2014).

Conclusion

Financial risks and crises are not just a major source of uncertainty but also a consequence of not taking uncertainty seriously enough (Aikman et al., under review). In analogy to the complex scenarios and oppositions played out in the domain of public health (Gigerenzer & Gray, 2011), we believe that all members of the financial community stand to benefit from simpler and more transparent regulations. As soon as enlightened customers—be it laypeople or professional investors—insist on comprehensible information and refuse to invest into financial products that they do not understand, financial institutions have additional incentives to offer simpler and more transparent products. This, in turn, facilitates the task of financial regulators and allows them to issue and enforce efficient and effective rules. Although the system's complexity and its inherent conflicts of interests present immense challenges, we trust that the virtues of simplicity are addictive enough to inspire and transform our current financial system.

References

Aikman, D., Galesic, M., Gigerenzer, G., Kapadia, S., Katsikopoulos, K., Kothiyal, A., Murphy, E., & Neumann, T. (under review). Taking uncertainty seriously: Simplicity versus complexity in financial regulation. *Bank of England*.

Akerlof, G. A., & Shiller, R. J. (2010). *Animal spirits: How human psychology drives the economy, and why it matters for global capitalism.* Princeton, NJ: Princeton University Press.

Andersson, P., & Rakow, T. (2007). Now you see it now you don't: The effectiveness of the recognition heuristic for selecting stocks. *Judgment and Decision Making*, *2*(1), 29–39.

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

Berg, N., & Gigerenzer, G. (2010). As-if behavioral economics: Neoclassical economics in disguise? *History of Economic Ideas*, *18*(1), 133–166.

Breiman, L., Friedman, J. H., Olshen, R. A., & Stone, C. J. (1984). *Classification and regression trees*. Belmont, CA: Wadsworth.

Camerer, C. F., Loewenstein, G., & Rabin, M. (2004). *Advances in behavioral economics*. Princeton, NJ: Princeton University Press.

DeMiguel, V., Garlappi, L., & Uppal, R. (2009). Optimal versus naive diversification: How inefficient is the 1/*N* portfolio strategy? *Review of Financial Studies*, *22*(5), 1915–1953.

Dhami, M. K. (2003). Psychological models of professional decision making. *Psychological Science*, *14*(2), 175–180.

Estrella, A. (2004). The cyclical behavior of optimal bank capital. *Journal of Banking & Finance*, *28*(6), 1469–1498.

Fischer, J., Steiner, F., Zucol, F., Berger, C., Martignon, L., Bossart, W., Altwegg, M., & Nadal, D. (2002). Use of simple heuristics to target macrolide prescription in children with community-acquired pneumonia. *Archives of Pediatrics & Adolescent Medicine*, *156*(10), 1005–1008.

Gaissmaier, W., & Marewski, J. N. (2011). Forecasting elections with mere recognition from small, lousy samples: A comparison of collective recognition, wisdom of crowds, and representative polls. *Judgment and Decision Making*, *6*(1), 73–88.

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

Gigerenzer, G. (2002). *Reckoning with risk: Learning to live with uncertainty*. London, UK: Penguin.

Gigerenzer, G. (2014). *Risk savvy: How to make good decisions*. New York, NY: Penguin.

Gigerenzer, G., & Brighton, H. (2009). Homo heuristicus: Why biased minds make better inferences. *Topics in Cognitive Science*, *1*(1), 107–143.

Gigerenzer, G., & Gray, J. (2011). *Better doctors, better patients, better decisions: Envisioning health care 2020*. Boston, MA: MIT Press.

Gigerenzer, G., Hertwig, R., & Pachur, T. (Eds.). (2011). *Heuristics: The foundations of adaptive behavior*. New York, NY: Oxford University Press.

Gigerenzer, G., Todd, P. M., & the ABC Research Group. (1999). *Simple heuristics that make us smart*. New York, NY: Oxford University Press.

Gilovich, T., Griffin, D., & Kahneman, D. (2002). *Heuristics and biases: The psychology of intuitive judgment*. Cambridge, UK: Cambridge University Press.

Goldstein, D. G., & Gigerenzer, G. (2002). Models of ecological rationality: The recognition heuristic. *Psychological Review*, *109*(1), 75–90.

Green, L., & Mehr, D. R. (1997). What alters physicians' decisions to admit to the coronary care unit? *Journal of Family Practice*, *45*(3), 219–226.

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

Haldane, A. G., & Madouros, V. (2012). *The dog and the frisbee* (Tech. Rep.). London, UK: Bank of England. (Speech presented at the Federal Reserve Bank of Kansas City's 36th economic policy symposium, "The Changing Policy Landscape", Jackson Hole, WY, August 2012)

Hertwig, R., Hoffrage, U., & the ABC Research Group. (2013). *Simple heuristics in a social world*. New York, NY: Oxford University Press.

Hutchinson, J. M. C., & Gigerenzer, G. (2005). Simple heuristics and rules of thumb: Where psychologists and behavioural biologists might meet. *Behavioural Processes*, *69*(2), 97–124.

Jacobs, H., Müller, S., & Weber, M. (2013). How should individual investors diversify? An empirical evaluation of alternative asset allocation policies. *Journal of Financial Markets*.

Kahneman, D. (2011). *Thinking, fast and slow*. New York, NY: Farrar, Straus and Giroux.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica: Journal of the Econometric Society*, 263–291.

Knight, F. H. (1921). *Risk, uncertainty and profit*. Chicago, IL: University of Chicago Press.

Lo, A. W., & Mueller, M. T. (2010). Warning: Physics envy may be hazardous to your wealth. *Journal of Investment Management*, *8*, 13–63.

Luan, S., Schooler, L. J., & Gigerenzer, G. (2011). A signal-detection analysis of fast-and-frugal trees. *Psychological Review*, *118*(2), 316–338.

Makridakis, S., & Taleb, N. (2009). Decision making and planning under low levels of predictability. *International Journal of Forecasting*, *25*(4), 716–733.

Mandelbrot, B. B., & Hudson, R. L. (2004). *The (mis) behavior of markets: A fractal view of risk, ruin, and reward*. New York, NY: Basic Books.

Markowitz, H. M. (1952). Portfolio selection. *The Journal of Finance*, *7*, 77–91.

Martignon, L., Katsikopoulos, K. V., & Woike, J. K. (2008). Categorization with limited resources: A family of simple heuristics. *Journal of Mathematical Psychology*, *52*(6), 352–361.

Martignon, L., Vitouch, O., Takezawa, M., & Forster, M. R. (2003). Naïve and yet enlightened: From natural frequencies to fast and frugal decision trees. In D. Hardman & L. Macchi (Eds.), *Thinking: Psychological perspectives on reasoning, judgment and decision making* (pp. 189–211). Chichester, UK: Wiley.

McLeod, P., & Dienes, Z. (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.

Meder, B., Le Lec, F., & Osman, M. (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), 257–260.

Neth, H., Khemlani, S. S., & Gray, W. D. (2008). Feedback design for the control of a dynamic multitasking system: Dissociating outcome feedback from control feedback. *Human Factors*, *50*(4), 643–651.

Neth, H., Schächtele, S., Duwal, S., & Todd, P. M. (2011). Competitive mate choice: How need for speed beats quests for quality and harmony. In L. Carlson, C. Hölscher, & T. Shipley (Eds.), *Proceedings of the 33rd Annual Meeting of the Cognitive Science Society* (pp. 699–704). Austin, TX: Cognitive Science Society.

Ortmann, A., Gigerenzer, G., Borges, B., & Goldstein, D. G. (2008). The recognition heuristic: A fast and frugal way to investment choice? *Handbook of Experimental Economics Results*, *1*, 993–1003.

Payne, S., Duggan, G., & Neth, H. (2007). Discretionary task interleaving: Heuristics for time allocation in cognitive foraging. *Journal of Experimental Psychology: General*, *136*(3), 370–380.

Petrie, M., & Halliday, T. (1994). Experimental and natural changes in the peacock's (Pavo cristatus) train can affect mating success. *Behavioral Ecology and Sociobiology*, *35*(3), 213–217.

Ratnovski, L., & Huang, R. (2009). Why are Canadian banks more resilient? *IMF Working Paper*, *9*.

Reinhart, C. M., & Rogoff, K. (2009). *This time is different: Eight centuries of financial folly*. Princeton, NJ: Princeton University Press.

Savage, L. J. (1954). *The foundations of statistics*. New York, NY: Dover Publications.

Serwe, S., & Frings, C. (2006). Who will win Wimbledon? the recognition heuristic in predicting sports events. *Journal of Behavioral Decision Making*, *19*(4), 321–332.

Simon, H. A. (1956). Rational choice and the structure of the environment. *Psychological Review*, *63*(2), 129–138.

Sims, C. R., Neth, H., Jacobs, R. A., & Gray, W. D. (2013). Melioration as rational choice: Sequential decision making in uncertain environments. *Psychological Review*, *120*(1), 139–154.

Taleb, N. N. (2010). *The black swan: The impact of the highly improbable*. New York, NY: Random House.

Taleb, N. N., & Sandis, C. (2014). The 'skin in the game' heuristic for protection against tail events. *Review of Behavioral Economics*, *1*, 1–21.

Thaler, R. H., & Sunstein, C. R. (2008). *Nudge: Improving decisions about health, wealth, and happiness*. New Haven, CT: Yale University Press.

Todd, P. M., Gigerenzer, G., & the ABC Research Group. (2012). *Ecological rationality: Intelligence in the world*. New York, NY: Oxford University Press.

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science*, *185*(4157), 1124–1131.

Vazquez, F., & Federico, P. (2012). Bank funding structures and risk: Evidence from the global financial crisis. *Available at SSRN 1997439*.

Von Neumann, J., & Morgenstern, O. (1944). *Theory of games and economic behavior*. Princeton, NJ: Princeton: Princeton University Press.

Wübben, M., & von Wangenheim, F. (2008). Instant customer base analysis: Managerial heuristics often 'get it right'. *Journal of Marketing*, *72*(3), 82–93.

Appendix
Author Information

Biographies

Hansjörg Neth is an adjunct researcher of the *Center for Adaptive Behavior and Cognition* (ABC) at the *Max Planck Institute for Human Development*, Berlin. Prior to his current appointment as acting chair of *Cognition, Emotion, and Communication* at the *University of Freiburg* he taught *Cognitive and Decision Sciences* at the *University of Göttingen*, was research assistant professor in *Cognitive Science* at *Rensselaer Polytechnic Institute*, USA, and holds a PhD in psychology from *Cardiff University*, UK.

Björn Meder is a research scientist at the *Center for Adaptive Behavior and Cognition* (ABC) at the *Max Planck Institute for Human Development* in Berlin. His research interests include judgment and decision making, causal inference, information search, and cognitive modeling. Björn holds a PhD in psychology from the *University of Göttingen*, Germany.

Amit Kothiyal is a post-doctoral fellow at the *Center for Adaptive Behavior and Cognition* (ABC) at the *Max Planck Institute for Human Development* in Berlin. His research interests lie in decision making under risk and uncertainty. Amit received a PhD in economics from the *Tinbergen Institute*, Netherlands.

Gerd Gigerenzer is director of the *Center for Adaptive Behavior and Cognition* (ABC) and the *Harding Center for Risk Literacy*, both at the *Max Planck Institute for Human Development*, Berlin. His most recent books are *Risk Savvy* (2014), *Ecological Rationality* (2012, with Peter Todd), *Heuristics* (2011, with R. Hertwig & T. Pachur), and *Better Doctors, Better Patients, Better Decisions* (2011, with Sir Muir Gray).

Contact Details

Address

Center for Adaptive Behavior and Cognition (ABC)
Max Planck Institute for Human Development
Lentzeallee 94
14195 Berlin
Germany

E-mails

neth@mpib-berlin.mpg.de
meder@mpib-berlin.mpg.de
kothiyal@mpib-berlin.mpg.de
gigerenzer@mpib-berlin.mpg.de