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UNCERTAINTY, DECISION SCIENCE, AND POLICY MAKING: A MANIFESTO FOR A RESEARCH AGENDA

ABSTRACT: *The financial crisis of 2008 was unforeseen partly because the academic theories that underpin policy making do not sufficiently account for uncertainty and complexity or learned and evolved human capabilities for managing them. Mainstream theories of decision making tend to be strongly normative and based on wishfully unrealistic "idealized" modeling. In order to develop theories of actual decision making under uncertainty, we need new methodologies that account for how human (sentient) actors often manage uncertain situations "well enough." Some possibly helpful methodologies, drawing on digital science, focus on the role of emotions in determining people's choices; others examine how people construct narratives that enable them to act; still others combine qualitative with quantitative data.*

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Policy decisions, practically defined for this paper as commitments to become dependent on the outcomes of longer-term and consequential relationships to chosen projects (rather than their perceived alternatives), are at the heart of politics, business, finance, health, defense, security, and our evolving physical environment. This is a paper about the current thinking informing policy making in this sense: what it takes for granted, its consequences, and what to do about it.

We start from the position that theories—and thus the research grounding them—affect policy making.[2] Policy makers tend to develop theories based not only on actual or anticipated social interaction, but also on (often-implicit) causal explanatory models of the world. Even when they are not aware of them, these models inform their perception of the situation at hand (Thomas 1923). Such models are encountered either directly, such as in business schools and university economics departments, or indirectly, as through the training of the decision makers' advisers.

Our second position is that many political decision makers have been relying, without sufficient examination, on advice based on standard economic models that have dominated decision science since the Second World War. The key feature of these standard models is that they are both idealized and "idealistic" (Katsikopoulos 2014). They are idealized or unrealistic because they tend not to be supported by actual observations of how reasonable people make decisions in real-world settings and are usually divorced from the uncertainty and complexity of implementation. The models are sometimes informed by data produced in laboratory experiments, but what makes them unrealistic is less the fact that the data are about artificial decision making settings with little at stake than that the data are processed via assumptions that treat people as always in a position to make unique optimal decisions, subject to any particular constraints which they may face. Such actors are effectively omniscient. They are given no scope either to suffer the problems of deciding how to interpret available information or to have doubts as to which model of the ways the world works they should best apply. Further, the models are "idealistic" because they represent agents who make decisions according to normative ideals regarding the role pure reason, logic, and objectivity *should* be expected to play in thinking and deciding. These normative "ideals" are grounded in a very narrow interpretation of rational thought, essentially limited to internal logical consistency, which excludes induction, creativity, imagination, and constructive emotions. Further, agents tend to be conceived as atomistic and thus as unaware of and unaffected by each other, except perhaps indirectly, through the anonymous decisions that lead to a certain price at a certain time.

There is nothing particularly "economic" about such an asocial conception of agency. Adam Smith, for example, thought that the desire to be "well regarded" was essential to understanding action, while David Hume thought that we act so as to satisfy our emotions. However, in contrast to Smith and Hume, contemporary economics—and even the cognitive psychology that is being used to amend contemporary economics—perpetuate an idealistic conception of agency.

The deficiency of these models became clear during the 2008 financial crisis. As the then-president of the European Central Bank, Jean-Claude Trichet (2010), put it:

> When the crisis came, the serious limitations of existing economic and financial models immediately became apparent. Arbitrage broke down in many market segments, as markets froze and market participants were gripped by panic. Macro models failed to predict the crisis and seemed incapable of explaining what was happening to the economy in a convincing manner. . . . As a policy-maker during the crisis, I found the available models of limited help. In fact, I would go further: in the face of the crisis, we felt abandoned by conventional tools.

Trichet was not alone in this view. The crisis should have sparked, in its turn, an intellectual crisis concerning the validity of policy advice.

We hope to take advantage of the opportunity provided by the financial crisis for rethinking decision-making models. We will sketch where, how, and why "idealistic" models failed (and why they are likely to continue to fail). We will also discuss possible research directions—such as the new opportunities presented by digital data and analytics—to create more realistic and effective models.

I. IDEALISTIC MODELS OF DECISION MAKING

Models of decision making tend to postulate one of two types of agents. The first, the idealistically conceived agent of standard neoclassical economics, uses the complete set of information that is available about any given decision in an optimal way; or, in situations in which the agent lacks complete information, he or she still makes the optimal decisions subject to this constraint (and other constraints such as inadequate resources or the behavior of others, as in Cournot-Nash equilibria). The second type of agent is the irrational agent conceived of by modern behavioral economics, who frequently deviates from making optimal decisions because of biases and framing errors.

Neoclassical Economics

Economics is essentially a theory of how agents choose amongst alternative options in any given situation. Like any theory, it makes assumptions that simplify reality. A simplification need not be unrealistic. The question, rather, is: To what extent are the assumptions reasonable approximations of the real world?

In standard neoclassical[3] economics agents are treated as if they know the model that correctly describes the behavior of the system in which they operate. Their goals are defined by the maximization of their expected utility and it is assumed that the information relevant to achieving a goal is available or can be axiomatically inferred. This view has no room for most of the real-world problems of uncertainty, conflict, and imperfect implementation that a typical policy maker may experience as relevant to his decision.

In addition to the assumption that agents are aware of *the* correct model, neoclassical economics contains several other unrealistic assumptions that can be gleaned from any mainstream textbook (e.g., Mankiw 1997). First, crucially, it is assumed that the agent—a person, firm, or government—has a set of stable preferences across the range of alternatives. In fact, the precise, formal assumption is much more demanding than this. The agent is assumed to have a set of preferences that are complete over all possible alternatives. However, even in its more relaxed, purely descriptive form, the assumption of stable preferences implies that agents' preferences do not change over time and, thus, that agents cannot and do not learn what they desire from experience.

A second key assumption is that an agent is not influenced directly by other people's decisions. This is, naturally, a peculiar assumption for any policy maker to sustain in the interconnected media-hungry world of the twenty-first century.[4]

A third assumption is that the agent has the computational capacity to gather and process all relevant information not only about the goods and services he sees, but about unseen alternatives. In the more general version, which acknowledges the existence of imperfect information amongst some or even all agents, there may be costs to cognition (the cost of gathering information and maybe of processing it). However, it still retains the principle that an agent is trying to optimize his actions, subject to the cost constraints. Therefore, if the agent is free of bias, among the options he can compute he will choose the one that maximizes utility. Thus, for example, in forming expectations about the future, over time these expectations will on average prove to be correct. They may not necessarily be correct in every single period. But the agent is presumed to be using the correct model of the system with which to form his expectations. Any errors that might emerge are therefore purely random, and will cancel each other out over time. On average, then, over an unspecified but long period of time, the expectations will prove correct. Since only firms that maximize utility will survive in a competitive context, it can be assumed that every firm that matters will make the right decision (Azar 2006). Conversely, consumers who make non-optimal decisions do not disappear, but they may experience lower levels of utility than they could actually get.

The ultimate expression of mainstream economic theory, based on these assumptions, is general-equilibrium theory. (The importance of general-equilibrium theory in economics is suggested by the fact that no fewer than seven out of the first eleven winners of the Nobel Prize in economics received it for their work on general equilibrium.) Its main contribution is to define a mathematical framework within which it can be shown that the individualistic optimizing behavior of economic agents can be coordinated on an equilibrium, provided that the public price signals are correct. Equilibrium is not to be understood here as the rest point of a dynamic system, as is standard in the natural sciences, but as an economic state in which supply and demand are balanced in every market such that there are no unused resources. In particular, if the market is at equilibrium, then any remaining unemployment cannot be said to be due to the deficiencies of the market; rather, according to the theory of general equilibrium, it means that the unemployed have rationally chosen not to work.[5]

General-equilibrium theory exercises a powerful influence on the policy recommendations made by economists. "Computable" general-equilibrium models are calibrated to specific circumstances, but the concept of general equilibrium has a wider reach. For example, in the past few decades the dominant trend within macroeconomics has been to produce Dynamic Stochastic General Equilibrium (DSGE) models.[6] These models are intended to help economic policy makers choose between options (as mentioned by Trichet). Although DSGE models are highly intricate and mathematical, they tend to rest on the incredible assumption that the whole behavior of a modern capitalist economy at the macro level can be modeled as the actions of a single agent—the "representative" agent. In the case of unemployment, the representative macro agent is thought to have made an optimal choice to consume leisure time instead of working. Naturally, since they contain only one agent, these models are unable to distinguish, for example, between the behavior of debtors and of creditors. One can readily see that in a financial crisis these models would be hard to apply and may have played a role in making the crisis hard to foresee (Ormerod 2010). Subsequent to the crisis, the models have been expanded to allow more than one agent, but they retain their other fundamental assumptions about unrealistic optimization.

Olivier Blanchard, chief economist at the International Monetary Fund, eulogized DSGE models in an MIT working paper published just three weeks before the collapse of Lehman Brothers in September 2008. Blanchard (2008, 24) wrote that "DSGE models have become ubiquitous. Dozens of teams of researchers are involved in their construction. Nearly every central bank has one, or wants to have one. They are used to evaluate policy rules, to do conditional forecasting, or even sometimes to do actual forecasting." He concluded his paper with the claim that "the state of macroeconomics is good." Despite the crisis, DSGE models continue to be influential and pervasive, particularly in policy analysis rather than pure short-term forecasting. For example, the website of the European Central Bank carries a description of its DSGE model. Dotsey 2013 describes its use in monetary policy by the Federal Reserve. Del Negro et al. 2013 describes the DSGE model of the Federal Reserve Bank of New York and "how the model works, how it is estimated, how it rationalizes past history, including the Great Recession, and how it is used for forecasting and policy analysis."

Behavioral Economics and Psychology

The central assumptions about how to model agents model in economics today are also the main assumptions in dominant approaches to modeling decision making in psychology. They are inspired by the same vision of the ideal, unboundedly rational creature postulated in neoclassical economics: Someone living in a world where he can consistently know not only what he wants but how to get it. A typical example is a choice among risky gambles. The decision maker is presumed to know all possible outcomes of each gamble, to assign a numerical utility to each outcome, to know the probability with which each outcome will occur, and finally to calculate the expected utility of each gamble so that she chooses a gamble that obtains the maximum profit.

The choices of an expected utility optimizer can be represented by the logical axioms jointly equivalent to expected utility theory (von Neumann and Morgenstern 1944). One type of axiom is that of transitivity, where for all gambles x, y, and z, if x is chosen over y and y is chosen over z, then x is chosen over z. Although sometimes transitivity and similar axioms are thought to have merely normative status such that a decision maker should satisfy them (Savage 1954; Wakker and Tversky 1993), they are generally viewed as empirical descriptions. The same kinds of axioms are the building blocks of the idealistic culture of modeling in psychology and in behavioral economics as well. A researcher can generate new models of bounded rationality by retaining some axioms of unbounded rationality, taking out others, and proposing new ones. For example, Daniel Kahneman and Amos Tversky's prospect theory always satisfies transitivity but may violate the axiom of independence, where for all gambles x, y, and z and probabilities p, if x is chosen over y, then the compound gamble (x, p; z, 1—p) is chosen over (y, p; z, 1—p) (Kahneman and Tversky 1979). Thus, the prospect theory decision maker is only slightly less idealized than her expected-utility ancestor.

In sum, idealistic models in psychology and behavioral economics tend to have three particular features: (1) they refer to decisions made in an imagined context where real uncertainty about what might happen in future is limited or quantified to what is usually thought of as risk (e.g., gambles where the probabilities of outcomes over a series of trials are known), not decisions under uncertainty (where the probabilities are not known); (2) they are not concerned with how decision makers make sense of or interpret a given "decision problem" (e.g., how people would come to frame a situation as a choice between risky gambles); and (3) they tend to neglect the role of non-cognitive factors, such as motivation, intuition, and emotion—or when these are referred to, they are seen as factors that upset optimal decision making.

More generally, idealistic decision models in psychology and behavioral economics often take as their point of departure mathematical facts, such as axioms and principles, rather than empirical findings. This may sound odd given that behavioral economists try to examine behavior experimentally. But empirical facts are not the sole—or in some cases even the primary—inspiration or justification for the development of idealistic models. For example, a key assumption of cumulative prospect theory—that people weigh probabilities nonlinearly—was inspired by the empirical fact that people's attitudes toward risk depend on whether they expect to gain or lose and on their estimated probability of the size of the gains or losses (Tversky and Kahneman 1992). But in addition to this empirical fact, the assumption that people weight probabilities was influenced by the general mathematical formula that utility is multiplied by probability, a common formulation in idealistic models. Although this assumption is not necessary to explain empirical behavior, as shown by other models that do not incorporate the assumption (Katsikopoulos and Gigerenzer 2008), some practitioners of behavioral economics think its empirical basis is firm enough that they advocate it as a prescriptive approach to how people *should* make decisions. The story goes as follows (Katsikopoulos 2014): People are systematically behaving irrationally, but because they are in principle able to figure out how to behave rationally, they should keep trying to do so. Interestingly, however, the proponents of the idealistic approach do not believe that people *can* actually learn to behave "rationally" (Bond 2009).

It is clear that those who buy this story will end up as frustrated as Tantalus ever was. This frustration is bound to lead to one of two dysfunctional responses: one can either deny, as neoclassical economists do, that people make bad decisions; or one can acknowledge, as behavioral economists tend to do, that people sometimes make disastrous decisions and recommend that they should therefore surrender to the designs of somebody smarter (who one hopes is also well meaning). The latter impetus is seen in the recent push for changing not the decision maker but the context in which decisions take place—"nudging," encouraging, or forcing people to make the "right" decisions (Sunstein and Thaler 2008) by altering the choice architecture within which options are presented. This paternalism (libertarian or otherwise) makes sense only if the nudgers or enforcers know both what is wanted and the best way to achieve it. It also depends on the assumption that real-world decisions will be similar to the decisions made in laboratory experiments, where enough necessary information is available to the participants that they can, in principle, make the "right" decision.

The Problems

A great deal of effort has gone into research on decision making. But as a spokesperson for the UK Cabinet Office recently noted, "the products of the research community are largely not relevant to our needs" (quoted in Rees and Whitaker 2014). This is not because the models are too simple. Models must simplify. Rather the problem is that idealistic modeling focuses on the wrong kinds of decisions (for example, on gambles where there is a well-defined answer) in the wrong contexts (in which interpretation and model uncertainty are off limits) with the wrong (i.e., idealized) agents. In particular, idealistic modeling has little or nothing to say about *how,* faced with a real situation with uncertainty about whether some means will produce a given end, an agent can optimize her utility.

It is unsurprising that, in consequence, for most policy-relevant contexts, the conclusions of such modeling are often misleading for several reasons. The first problem is that idealistic modeling always assumes a context where it is possible to calculate the best decision at any point in time. The investigators know the best decision, after all—or so they assume! This implies that laboratory decision makers have a level of knowledge about future outcomes and knowledge about how to obtain what they want that is quite impossible to imagine in most real-world policy contexts. More usually policy makers and those they seek to influence are faced with ontological uncertainty (Giddens 1991; Lane and Maxfield 2005): They are often uncertain about the validity of their own beliefs about what will happen. Likewise, policy makers are uncertain (or should be uncertain) which policies will or will not be effective. In such situations, the actors are not necessarily making framing errors or biasing their decisions away from the "right" one. They just can't know what it would be best to do. Ontological elements (objects and the connections between them) are themselves hard to grasp, rendering uncertain which frame is the "correct" one, which decision the "right" one, or even the range for which probabilities might be assigned. Ignoring the dangers of assuming that we know more than we do has been disastrous. As John Kay (2011, 173) puts it, "It is hard to overstate the damage done in the recent past by people who thought they knew more about the world than they really did."

A second, related source of difficulty is that idealistic modeling ignores the need for interpretation and for the management of irreducible conflicts between competing means to the same end. Most decisions of this sort depend on information that is not just incomplete but hard to judge in and of itself. Interpretations can also change. No matter how many facts one knows about a given economy or about climate change, the significance of an economic or climatic problem, its causes, whether they can be ameliorated, and if so, by what means are all open to reasonable question.

A third source of difficulty concerns the poverty of the idealized conception of a decision-making agent. If decision making is seen to require merely the optimization of large volumes of available information, without any need to interpret the data, then the best decision maker will be an isolated computer or programmed robot that has no use for the many evolved human capabilities that assist interpretation and action—such as inference, emotion, imitation or narrative, or more generally the capacity for social interaction, trust, and social influence—which, on the idealized view, may even put human beings at a disadvantage. New developments in neuroscience and psychology, however, suggest that the traditional view of emotion and reason as antagonistic is mistaken and that in general, cognition is grounded in the body, such that emotional reactions (ultimately registered in various brain areas) play a vital role in perception, interpretation, simulation, and judgment, making action under uncertainty possible (Barsalou 2008; Blanchette and Richards 2010; Clark 1997; Damasio 1999; Edelman 2004; Gallese and Lakoff 2005; Tuckett 2011).

An implicit premise of dominant economic models is that the future will resemble the past. This may be true in routine situations. However, as Herbert Simon (1978) pointed out, "two generations of economic theorists" have grown a vast garden of formal and technical problems that rely on the assumption that the future will be like the past, and in so doing they have "postponed encounters with the inelegancies of the real world." Real-life decision makers have to imagine futures and figure out *to what extent* the future will be similar to the past. They suffer from an excess of information that might be relevant to predicting the future and they suffer from massive uncertainty about which aspects of this information to attend to, to treat as reliable, and to weigh as likely to be useful and relevant to their task, which is to work out how things done now will evolve in the future.

Idealistic models work only in ideal contexts, where it is reasonable to suppose the information currently available is not only all the information one needs, but that it also has a single correct interpretation. As Michael Woodford (2011) points out, even if a modeler chooses the model that he believes to be the most appropriate one and assumes that the agents in his model behave "rationally," he has no reason to believe that the real agents in question would choose the same model and thus share his expectations. Insofar as the modern world creates challenges that are complex rather than routine (Malleret 2012), the "idealistic" approaches just described seem to us not only to be of very limited value but also to be dangerous. They have a tendency to provoke "paralysis by analysis" and either helplessness or hubris in the face of uncertainty.

Thus, in the past seven decades, the decision-making models that have been produced have been mostly unhelpful since they have been dominated by idealistic modeling of questionable relevance. What we need are not more modeling resources but better theoretical frameworks to understand choices made under uncertainty.

II. NEW OPPORTUNITIES, NEW FRAMEWORKS, AND NEW APPROACHES

The standard idealistic approaches we have been reviewing are not the only ones to have been developed. More promising approaches have existed for some time.[7] However, they have failed to gain traction or attention in the academic community. In this part of the paper we want, first, to argue that it is important to develop a much more pragmatic and less mathematically axiomatic science of decision making supported by empirical research in relevant contexts; and, second, to describe some recent cutting-edge approaches to doing just that.

We suggest that the following principles should guide future research efforts:

1. Theories should be clearly supported by the study of "in vivo" decision making, with much more emphasis on seeking to understand processes in ontologically uncertain contexts that are relevant to policy making. This implies a focus on non-routine rather than on routine decisions, long-term rather than short-term decisions, complex rather than simple

decisions, and decisions made in teams rather than by isolated individuals.

2. Theories should be supported by studies that take account of a much wider range of relevant human capacities obviously available to the agents who make decisions, such as feeling, imagining, interpreting, co-operating, and imitating, not just calculating.
3. Theories should be based on studies that go beyond one-shot decisions to examine processes of managing decision making over time. We need to explore the influence of the social and psychological processes that enable decision makers to gain support for decisions made under uncertainty, when psychological and social pressures may make it difficult to take any long-term decisions at all, *and* to examine how they monitor the outcome of what they are deciding and adjust and learn from experience. This would include attending to the unintended outcomes of decisions; for example, by studying the effects of regulatory actions in finance or the economy and comparing them to intentions.
4. Theories should take account of the wider decision-making context, in particular the ways decisions are embedded in social practices, how formal and informal institutional processes shape decisions, and how multiple actors and their decisions are interdependent. This would include investigating the facilitating tropes and images that various actors bring to bear in their practical engagements with complex circumstances.[8]

Research that embraces such features will need to be genuinely interdisciplinary (covering perspectives from economics, social and brain sciences such as social and cognitive psychology, neuroscience, linguistics, psychoanalysis, and even literature and poetry) and will need to study how decisions are actually made. With this kind of effort we could expect to build new reality-based theories of decision making that are useful in understanding the consequences of different ways of making decisions that matter.

In what follows, we highlight a few ongoing research projects that, in our view, exemplify new reality-based theories of decision making. The first of these examples shows the advantage of considering the context in which decisions are made. The second illustrates what might be accomplished by operationalizing a theory designed for a context of ontological uncertainty populated by more broadly conceived human social actors. The third shows the potential benefit of re-examining traditional quantitative/qualitative research boundaries, while the fourth puts quantitative efforts to anticipate the uncertain future alongside those used in scenario development.

The Pragmatic "Adaptive Toolbox" Approach

The "pragmatic" adaptive-toolbox approach to decision making, being developed at the Max Planck Institute for Human Development in Berlin (see Gigerenzer et al. 1999), looks at decision making in its particular context. Rather than making generalizations about decisions based on the features of one type of decision made in one time and place, this approach examines the match between a particular heuristic (i.e., a simple mental shortcut or rule of thumb) that one uses in order to make a decision (e.g., decide based on just one reason) and the environment or "ecology" in which it works. It thus focuses on "ecological rationality" rather than the context-free formal logical rationality championed in economics. The outcome is an experimentally and analytically supported account of which tools work best in which specific circumstances.

The pragmatic approach empowers actors to identify and use what they already know insofar as it works in their context. Its research base is an extensive set of empirical findings describing how people make decisions, not only in the laboratory but also in the field (e.g., how consumers choose which electricity carrier to use; Pichert and Katsikopoulos 2008). It also relies on a set of analytical findings showing how various heuristic tools work very well in various specific contexts but not in others.[9] In short, the story told in the pragmatic approach is that people use heuristics *and* that in many settings this is reasonable since they perform quite adequately—better, in fact, than standard decision-theoretic models such as linear models, Bayesian networks, classification and regression trees, etc.

In a variety of complex decision-making situations pragmatic approaches, using "one-reason" heuristics, have been shown to work better than idealistic solutions.[10] In medical clinics, for example, doctors must use "decision trees" to choose a diagnosis from among several options and determine which treatment is suitable. Deploying idealistic approaches, Bayes's rule can be represented as a tree with 2^m branches, where m is the number of binary cues or attributes (e.g., whether a medical test, such as a mammography, indicates a disease or not). Yet when the number of cues grows, a Bayesian approach becomes computationally intractable or fraught with estimation error because one typically has too few data points for the thousands of branches of such a gigantic tree.

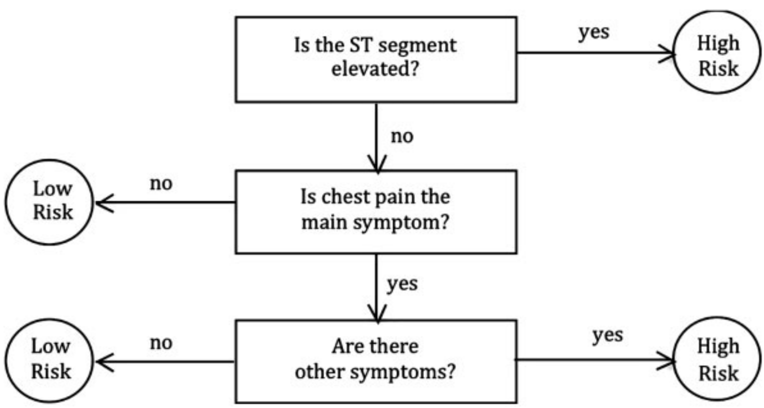
In contrast, a fast-and-frugal tree has only (m + 1) branches and thus is likely to be more robust. It has the following building blocks (Martignon et al. 2008; for an example, see Figure 1 below):

1. A searching rule: Search through cues in a predetermined order.
2. A stopping rule: Stop search as soon as a cue leads to an exit (i.e., allows a classification to be made).
3. A decision rule: Classify the object accordingly.

Fast-and-frugal trees are used successfully by experts in many fields, from cancer screening to making decisions about whether to allow a defendant to post bail. Laura Martignon and colleagues (2008) tested the accuracy of fast-and-frugal trees in 30 classification problems ranging from fields such as medicine and sports to economics. They reported that complex benchmark strategies, including logistic regression, excelled at data fitting, but fast-and-frugal trees were close or identical to these strategies in their predictive accuracy.

A specific example is emergency medicine. When patients arrive at the hospital with severe chest pain, emergency physicians have to decide

Figure 1. Fast-and-Frugal Tree for Categorizing Patients' Risk of Having Ischemic Heart Disease



Source: Adapted from Green and Mehr 1997.

quickly whether they suffer from acute ischemic heart disease and should be assigned to the intensive coronary care unit (ICU). In a Michigan hospital, doctors preferred to err on what they believed was the safe side by sending about 90 percent of the patients to the ICU, although only 25 percent of these actually had a myocardial infarction (Green and Mehr 1997). The result was an overly crowded ICU, lower quality of care, higher cost, and a risk of serious infection among those who were incorrectly assigned. Green and Mehr (1997) tried two solutions: (a) a logistic regression, the Heart Disease Predictive Instrument, and (b) a fast-and-frugal tree. To use the Heart Disease Predictive Instrument, doctors received a chart with some 50 probabilities, checked the presence and absence of symptoms, and inserted the relevant probabilities into a pocket calculator. The fast-and-frugal tree ignored all probabilities and asked only a few yes-or-no questions. Ultimately, the tree was more accurate in predicting actual heart attacks than was the Heart Disease Predictive Instrument: It sent fewer patients who suffered from a heart attack wrongly into a regular bed and also nearly halved physicians' high false-alarm rate. Last but not least, the tree was transparent, easy to memorize, and easy to modify, and was accepted by physicians who disliked relying on a logistic regression they barely understood. The tree is presented in Figure 1.

More recently, fast and frugal trees have also been applied to the domain of financial regulation (Aikman et al. 2014). Using a dataset of 116 global banks, which had $100 billion in assets at the end of 2006, fast and frugal trees, and the logistic regressions typically used in such analyses in finance, were employed in order to predict which of 43 banks failed (i.e., went bankrupt or had to be bailed out) during the crisis. A main result is that the performance of the two classes of algorithms was comparable, with the fast and frugal trees performing overall better under the more realistic condition of fewer economic indicators of high reliability being available.

Insofar as these new pragmatic approaches clearly have value, we need to understand why the idealistic culture has been so dominant and remains so attractive and so resistant to change despite its impracticality and its relative lack of empirical support (Katsikopoulos 2014). Perhaps approaches that draw on shortcuts, narratives, and emotions tend to be stigmatized in the academic community. They are undoubtedly depicted as less scientific, less elegant, and more irrational than more quantitative "rational-scientific" approaches. Furthermore, in contrast to pragmatic approaches, which offer reactive solutions to immediate problems, rational-scientific models maintain the illusion of agents' near omniscience.

The Conviction Narrative Approach

Conviction Narrative Theory (CNT) (Chong and Tuckett 2014; Tuckett et al. 2014a) is another attempt to operationalize a new theory of decision making, drawing on ideas developing in the fields of narrative and embodied cognition. It asks how, if people cannot be sure if the outcome of what they decide is gain or loss, they manage to commit to action. Decisions of the kind policy makers attempt will, of course, turn out to be successful or not, but that is not known in advance. To make decisions people have to interpret the facts they search out, to imagine how things will turn out for *them*, and to *feel* convinced about their conclusions. Keeping control of "the narrative" defining what is or not success may also be important in any eventual evaluation.

Specifically, CNT draws on what we are coming to know about the role played by emotion in facilitating action. In this approach, interpretations about the world and its future evolution are conceived as constituted through embodied narratives (Wojciehowski and Gallese 2011), which create good (satisfying = approach) or bad (frustrating = avoid) feelings registered in psychological and brain systems. Emotions related to the category of approach ("excitement about gain") will lead agents to embrace projects; emotions related to the category of avoid ("anxiety about loss") will lead to aversion. To act requires that explanations and arguments be available to repel anxiety.

CNT provides a research opportunity now that many decisions are reported in digital texts and large amounts of text can be processed very rapidly. Narratives about particular topics (e.g., housing) or locations (e.g., the United States) will often contain words that are well established in sociolinguistics to evoke the emotions of excitement about gain and anxiety about loss. The prediction is that shifts taking place through time in the relationship between these two types of words in a relevant body of narratives will mark underlying shifts through time in interpretations of the world. A financial bubble, for example, will be accompanied by a growing and disproportionate level of excitement words relative to anxiety words in relevant narratives (about dotcoms, mortgages, etc.), which will then "correct" when the bubble bursts. Over a whole economy a shift in the direction of more anxiety words relative to excitement words could indicate an underlying move towards less confidence played out shortly in a downward movement in GDP.

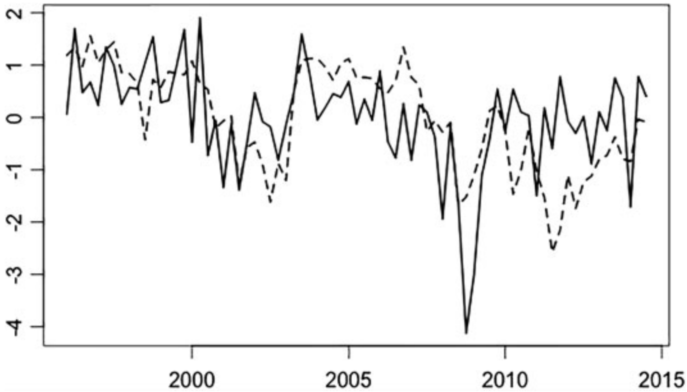
Over a fifteen-month period, a team at University College London used this cross-disciplinary theory of decision making under uncertainty to create a prototype analytic method called Directed Algorithmic Text Analysis (DATA) (Tuckett et al. 2014b; Tuckett et al. 2015). DATA extracts information about highly specific changes in expressed emotions in the narratives collected in digital text archives. The prototype creates what is called a relative sentiment shift (RSS) time series. This calculates changes, in any text database across time, in the number of words related to the category of excitement relative to the number of words in the category of anxiety, adjusting for the number of words in the articles, etc. Results suggest that this form of analysis has strong potential for improving our understanding of what is happening in the economy and where policy action might be required.

One digital data source is the Reuters News Archive, which spans 1996 to 2013 and contains over 14 million text documents. Figure 2 shows a relative sentiment shift time series generated from all texts originating in the United States (dashed curve) plotted against US GDP (solid curve). The sharp drop in GDP in the recession of 2008–9 is evident. It is equally evident that relative sentiment series begins to fall well in advance of the decline in GDP. The decline in GDP began in the second quarter of 2008 and was not predicted by conventional economists at the time. Indeed, consensus economic forecasts were still showing positive growth well into 2009. RSS series developed over several text databases consistently function as leading indicators of changes in both GDP and indices of uncertainty (Nyman et al. 2014; Nyman and Ormerod 2014; Tuckett et al. 2015). (In more formal terms, RSS series reflect Granger causality.)

What might explain these results?

The forecasting accuracy of the current, idealistically based economic models has long been recognized as poor, especially at what prove to be turning points—precisely when they are needed the most (Fildes and Stekler 2002; Zarnowitz and Braun 1992). The inability to predict the recent crisis is but the latest example (Bank of England 2008, 367, chart 8). We think the prototype RSS analysis is a useful indicator of what is happening in an economy because it is based on a wider conception of economic agents, who are viewed as constructing embodied narratives of conviction on which to base their actions. Specifically, it captures shifts

Figure 2. Quarterly percentage changes in U.S. Real GDP and Relative Sentiment Shifts in Reuters U.S.-Based News Articles



Source: Thomson Reuters News Archive
The solid line is the quarterly percentage change in real U.S. GDP. The dashed line is the relative sentiment series. Both series are normalized for purposes of comparison.

between two key groups of emotions that are important in the narratives people construct in order to act in situations of uncertainty. To act we need to *feel* convinced that we are making the best available decision. Our emotions often feel persuasive to us and often seem to us to be good guides to action because they are part of a larger narrative. For example, we might feel anxious if we think we may be in a dangerous situation. In this sense emotions, which are generally intertwined with particular (perhaps implicit) narratives, are the basis of actions. Therefore, an unusual shift from one category of emotion to the other may indicate that the basis on which action is being taken—the narrative undergirding the emotion—is also changing.

Thus, Conviction Narrative Theory does not treat thinking and feeling as opposed categories. Following developments in sociology, anthropology, psychology, and neuroscience, it recognizes that cognition and emotion are mutually supportive in permitting someone to act. In this approach, people perceive the world by constructing and refuting narratives that concern social relationships. People make sense of their observations by constructing narratives, and the narratives also help direct their attention. Narratives that "feel" right, perhaps because they make sense of the world, are strong determinants of economic action. Conviction Narrative Theory and DATA are thus attempts to operationalize a non-idealistic approach to understanding the aggregate outcomes of actions that together make up a variable, for example, GDP.

Two features of the prototype RSS measures developed to date are particularly important for forecasting. First, analyses of even very large textual databases can be performed quickly, in not more than a few hours, enabling them to be used as leading indicators for economic time series in a subsequent period. Second, unlike many economic time series, the RSS is not subject to revisions. The Reuters newsfeed text database in any given month, for example, contains articles that are not revisited and revised; nor are additional articles later added to it.

New Social Science

Policy analysis seeks to understand how to influence individuals in society. The analytical distinction between micro interactions and macro structure has inspired thinking about society ever since Durkheim (1912) defined social facts as sui generis. Tomasso Venturini and Bruno Latour (2010) have recently been studying the micro/macro distinction in the light of the large number of digital traces people leave when they cross borders, use their credit cards, meet each other, search the Internet, tweet, and so on. By following these traces we can see social groups forming and dissolving and barriers opening and closing.

Before the advent of digital traces, social scientists often had to choose between quantitative methods (monitoring large populations, but with only superficial insights) and qualitative methods (offering rich information, but only on small populations). Little by little, this methodological discontinuity trenched a theoretical divide between theories of micro interactions (supposedly local and subjective) and macro structures (supposedly global and objective). Instead of questioning this divide, idealistic models have proposed a number of ingenious (but unrealistic) ways to simulate the emergence of the global from the local; in economics this produced the "representative agent" of DSGE models.

According to Latour et al. (2012, 590), the traceability of digital media has transformed this situation, finally providing the data necessary to follow with continuity the weaving of collective life. "Once we have the experience of following individuals through their connections it might be more rewarding to begin navigating datasets without making the distinction between the level of individual component and that of aggregated structure." Digital traces offer us the ability to observe social phenomena in the making, thus erasing the hard-and-fast distinction between the individual and collective levels.

Digital tools allow us to conceive of society as formed by overlapping monads—a concept introduced into sociology by Gabriel Tarde (1893) and defined by Latour et al. (2012, 598) as "not a part of a whole, but a point of view on all the other entities taken severally and not as a totality." This approach might make it possible to develop different types of social science that emphasize that individual and collective actors are the result, not the premise, of social interactions. One illustration of the qualities of this quali-quantitative approach is the project *La Fabrique de la Loi* ("The Law Factory").[11] This project is meant to help citizens follow how French laws are transformed by parliamentary discussion. The current online platform contains data on about 300 proposed laws. It allows one to compare how much time each proposal occupied in the different sections of the parliament; to explore how each article of each law has been modified at each stage; to learn which amendments were proposed by different political groups; and to read the transcripts of parliamentary speeches on specific articles at specific stages of the discussion. Through these functions (and others), the platform encourages its users to navigate the datascape of the parliamentary discussion, zooming out to compare hundreds of laws' texts and zooming in to read verbatim transcripts of single discussions. One can thus observe both the structures of the French juridical system and the individual interactions in the parliament, which shows how the collective and individual levels are just two extremes of a seamless collective movement through which the law is constructed.

La Fabrique de la Loi is just one project that allows us to see the continuity of social existence. The same continuity has been illustrated by studies of how memes spread (Leskovec et al. 2009);[12] fame in the blogosphere (Cardon et al. 2011); migrant communities (Crush et al. 2012, 345);[13] manga styles (Manovitch 2012); scientific paradigms (Chavalarias and Cointent 2009; Börner 2010); open-source collaboration (Heller et al. 2011); international negotiations (Venturini et al. 2014); lexical trends in the history of literature (Michel et al. 2011); and Wikipedia controversies (Borra et al. 2014, 34).[14] All of these projects show how the continuum between local exchanges and global trends revealed by the advent of digital traces is much more interesting and rich than are its extremes. Social existence does not jump from micro to macro and neither should social sciences.

Foresight

Policy makers have to try to foresee the future, in part to figure out how it might be affected by a given policy. The activity of "foreseeing" or of creating "anticipatory knowledge" is challenging in many domains and can be seen in different ways (Selin 2008). For example, is the problem a deficit of knowledge about the future or is it a matter of irreducible uncertainty (Funtowicz and Ravetz 1993)? If the former, will a combination of better data and enhanced modeling enable effective change, or do new approaches need to be designed for managing societal transformation (as opposed to being designed for mere incremental change)? If the latter, how can policy makers and scholars determine the rigor and robustness of foresight about an issue or problem when they cannot yet access the facts of the future?

Foresight is an organized process of thinking about the future. Over the past sixty years the search for ways to appreciate, understand, and navigate complex challenges and future uncertainties has generated a diverse range of approaches to foresight. They reflect the different purposes and situations in which such practices are effectively deployed and they use a diversity of methods. These include computer-based modeling and simulation, forecasting, back-casting, visioning, scenario planning, horizon scanning, Delphi techniques, search conferences, etc. Each method is elaborated through a variety of techniques. Regardless of the method used, foresight practitioners recognize that before decision making, there is an important process of judgment: how the problem or situation is framed and by whom.

Under the idealized influences we have been discussing, in recent decades foresight thinking and practice have been threatened by the rise of quantitative forecasting and prediction, which have crowded out the alternative approaches represented by open-futures thinking and narrative-based inquiry. Quantitative forecasting uses historical data in the form of time series to suggest possible futures based on past patterns. Models based on idealized assumptions use statistical relationships derived from past data to extrapolate patterns from it (Montgomery et al. 2008), in some instances in the form of a fan diagram. The suppressed but familiar assumption is that the dynamics that produced the past will also produce the future. Joined to this assumption is the further implication that the future is closed and that there is little scope to shape it through human agency.

In contrast (perhaps in addition) to this type of quantitative forecasting, policy makers can use the activity termed "foresight" to see the future as the uncertain outcome of a playing field of power in which policies are strategically framed. One framing technique is the creation of plausibility-based scenarios, which offer an alternative approach to forecasting and policy choice that helps groups and organizations engage with unpredictability and uncertainty and cope with what we do not and cannot know (Wilkinson et al. 2013). For example, the Organization for Economic Cooperation and Development (OECD) is using the plausible-scenario approach to rethink the future of higher education (OECD 2009a), the future of international migration to OECD countries (OECD 2009b), and the future of pension incomes (OECD 2013) while the British government is using scenarios to anticipate how to address public-health issues, such as obesity (Butland 2007). While foresight exercises help us with the vital task of keeping open the potential for uncertainty in decision- and policy-making processes, it is particularly challenging to do so if those involved fail to recognize the limitations of the apparently more precise idealistic models.

In the approach to foresight termed "open futures thinking" and "narrative-based inquiry," the challenge is not better prediction of the future, so to speak, but the production or shaping of a world created by reflexivity (Beck et al. 1994), i.e., an enactment of the notion that "the situations that men define as true, become true for them" (Thomas and Thomas 1928, 572). Action is part of a whole process of creating, revealing, and testing deeply held assumptions (including mindsets, worldviews, and paradigms), managing disagreement (which is more often an asset than a disadvantage), and identifying more and better options. In essence, this new type of foresight recognizes the future as fiction in the making rather than as established fact.

III. POTENTIAL, RISKS, THEORIES, AND POLICIES

A salient feature of two of the projects introduced above is that they take advantage of the analytic potential of digital data. Thus they build on the fact that an exponentially growing share of social activities is recorded digitally and automatically in a form that is much easier to analyze than hitherto. Whereas once investigators would need to laboriously search through archives, conduct interviews, and make observations that often had all kinds of sampling problems, the advent of digital "Big Data" is an opportunity for more-comprehensive and less-onerous research. Digital data-intensive research can be used for generating, refining, and assessing hypotheses about complex systems in a rapid, iterative manner—thereby supporting exploration and complementing and facilitating more traditional scientific processes of hypothesis generation and experimental testing to provide strong causal inferences. The digital revolution creates new and more varied data (quantitative; qualitative; sentiment; micro; macro; etc.), enhances the scope for large-scale simulation and testing, and may enable early warnings and the fine-tuning and monitoring of actions or policies.

However, there are also perils. In particular, Big Data creates the possibility of finding a large number of spurious, artificial correlations, which, from the perspective of frequentist statistical theory, may appear, on conventional criteria, to be significant. If we do not posit theories before we haphazardly sift through the data, we may "find" hypotheses post hoc, but we then have no way of testing them since the process of finding them was the only available test. Finding a significant result that was not hypothesized before should be the beginning of a new effort, not the end of a previous lucky one. Big-Data researchers must also to do more than try to improve the probability of decision outcomes; they should also attempt to uncover deeply held interpretive frames and test the quality of interpreters' judgments. Finally, although this is a much larger subject than we can treat adequately here, we need to be very cautious when using machine learning techniques to analyze, understand, and model human choices using Big Data. The defining characteristics of Big Data are its volume, variety, and velocity. Machines can analyze large volumes of data and identify trends and apparent relationships very rapidly. But the techniques that allow for such high-speed analysis of great data volumes are often precisely those we have been questioning: optimization techniques based on pre-specified models (for instance, those with assumed normality of random variations), which are valid only insofar as the phenomena being analyzed are predictable rather than deeply uncertain. The danger is that superior machine capacities for rapid calculation and optimum selection are mistaken as superior to or reflective of human choice processes.

This is especially so if one thinks, as at least implicitly many behavioral economists do, that decision making goes awry because the human mind is distracted rather than assisted by emotions, sensations—the mind inside the mind. All too often an implicit and unrecognized aim of behavioral economics is to make human decision-making more like machine decision-making, which work well only when the problem is well defined. As we have been contending, many situations—particularly those involving uncertainty—are just not like that. But given the intractability of human "biases," it is all the more tempting to turn to machines rather than attempting to make machines more like people.

Overcoming Idealistic Modeling

Idealistic models, with their apparent ability to provide numbers and solutions, have great powers of recovery. Although Herbert Simon's seminal paper on behavioral economics, written in 1955, argued that heuristics both gave "satisfactory" outcomes and were actually used in most situations, the effect of his paper on economic thinking was minimal. Introducing his notion of "bounded rationality," he declared that "the task is to replace the global rationality of economic man with a kind of rational behavior which is compatible with the access to information and computational capacities that are actually possessed by organisms, including man, in the kinds of environments in which such organisms exist" (Simon 1955, 99). Although Simon's work led eventually to the development of both experimental and behavioral economics, the concept of bounded rationality was absorbed by the economics mainstream, which defanged it by transforming it into "optimization under computational constraints." Frank Knight's, J. M. Keynes's, and G.L.S. Shackle's arguments for the importance of uncertainty suffered similar fates. However, with the increasing awareness of the importance of "black swans" (e.g., Taleb 2010), economists and others are now paying more attention to the nature of uncertainty.

One explanation for this change is that theories informed by rational-scientific methodologies achieve credibility when underpinned by confident narratives about progress; that is, when convincing visions of future success seem to guarantee strategic grasps of complex fields. However, when (as now) the sense of progress begins to wear thin, people become more interested in detailed ethnographic observation of the cognitive and emotional processes driving reactive decision making (in finance or policy making, for example) (see Abolafia 1996).

Another way of thinking about the difficulties of changing idealist economic thinking is to recall that there is sunk human capital—financial and emotional—in the status quo. There is a massive investment in appearing to "know" and in idealistic approaches to knowing. Unlearning and facing how uncertain things are is hard and is thus a significant barrier to change. But it will never happen if we do not think about the limitations of existing approaches and recognize that there might be alternatives.

NOTES

1. This paper summarizes some of the main lines of discussion from a meeting in Florence that brought together physicists, computer scientists, psychologists, anthropologists, mathematicians, sociologists, economists, climate scientists, practitioners, and policy makers. We discussed decision-making processes, how "idealized" modeling prevents an adequate understanding of these processes, and alternative methodologies for a new understanding of them. The meeting was funded by the EU FP7 Co-ordination Action grant 266723 Global System Dynamics and Policy (GSDP), whose support is gratefully acknowledged. David Tuckett also wishes to acknowledge support from the Institute of New Economic Thinking (grant no. IN01100025) and the Anna Freud Centre. A follow-up meeting was generously aided by the University Paris 1 Panthéon-Sorbonne and the EU Co-ordination Action grant 296777 NonEquilibrium Social Science (NESS)
2. Power and politics may affect which theories gain acceptance, but such a discussion is beyond the scope of this paper.
3. These days, "neoclassical" economics is taken to be synonymous with "mainstream" economics.
4. See, for example, Ormerod 2012.
5. The formal articulation of general-equilibrium theory is highly mathematical, but for those interested a classic reference is Arrow and Hahn 1971, devastatingly criticized by Kirman 1989.
6. For a useful survey, see Tovar 2009.
7. See, for instance, Klein 1993; Bruner 1986 and 1990; Weick, Sutcliffe, and Obstfield 2005; Beach 2010.
8. A good example is the image of "the edge" (see Lyng 1990 and 2005) that risk-takers often crystallize in the course of their uncertain practices. The device of the edge partitions complexity into imagined spheres of greater or lesser rational controllability, helping actors distribute their decision making (rational and intuitive) according to the relative proximity of the edge.
9. For a review of research on heuristics, see Gigerenzer, Hertwig, and Pachur 2011.
10. For a review, see Katsikopoulos 2011.
11. See http://www.lafabriquedelaloi.fr/
12. See memetracker.org
13. See e-diasporas.fr
14. See contropedia.net

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