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Toward a cognitive science of markets: economic agents as sense-makers

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Abstract
Behavioral economics aspires to replace the agents of neoclassical economics with living, breathing human beings. Here, the author argues that behavioral economics, like its neoclassical counterpart, often neglects the role of active sense-making that motivates and guides much human behavior. The author reviews what is known about the cognitive science of sense-making, describing three kinds of cognitive tools—hypothesis-inference heuristics, stories, and intuitive theories—that people use to structure and understand information. He illustrates how these ideas from cognitive science can illuminate puzzles in economics, such as decision under Knightian uncertainty, the dynamics of economic (in)stability, and the voters' preferences over economic policies. He concludes that cognitive science more broadly can enhance the explanatory and predictive quality of behavioral economic theories.

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1 Introduction

The complaint has now been well-rehearsed: The agents of neoclassical economics are unbounded—rational, patient, and selfish—whereas the earth is populated with humans who are, to varying degrees, biased, impatient, and generous (e.g., Kahneman, 2002; Mullainathan & Thaler, 2002; Simon, 1955; Thaler, 2015). Behavioral economics thus came into the world and enriched our conception of what economic agents are (in)capable of, seeking to populate models with *homo sapiens* rather than *homo economicus*. This has been of course a great theoretical achievement, paying practical dividends in the design of public policy (e.g., Sunstein & Thaler, 2008).

But that achievement does not go far enough. This is because the economic agents of both neoclassical and behavioral economics lack one very human feature—they don't think. By this I don't mean that they lack input–output functions linking decision problems to choices—they do. What they lack is *internal states*, such as beliefs and expectations with a modicum of psychological realism, with models instead tending to assume that expectations are model-conforming and beliefs are Bayesian (e.g., Muth, 1961). Douglass North argued that the failure of economics to appropriately model beliefs was a central shortcoming of the discipline, noting that "it is modeling beliefs that is at the heart of all theorizing in the social sciences" (North, 1996, pg. 1). To a significant extent, both neoclassical and behavioral models treat humans as black boxes, much like early behaviorist models in psychology (e.g., Skinner, 1953; Watson, 1913), with the behavioral models perhaps better matches to individual behavior, but frequently failing to model what is going on in the agent's mind.

Why does this matter? Because humans are, yes, finite in processing power and biased in many decisions, but they are also adaptive learners, actively trying to understand their environment. Treating humans as static processors of information—whether optimal or not—leads to explanations of behavior that are incomplete or incorrect and models that often fail to make sound predictions. These shortcomings are common to neoclassical and to behavioral economics. Economics needs to take account of *cognitive science*—the study of how the mind processes information—in order to adequately understand how economic agents actively seek to understand and act on their world.

2 Three Economic Puzzles

In this article, I review what is known about the cognitive science of sense-making as it relates to economic phenomena. In reviewing this research, I look at three representative categories of economic puzzles, ranging from the micro level (individual decision-making under Knightian uncertainty) to the macro level (economic instability and economic policy decisions).

First, *decision-making under Knightian uncertainty*. Whereas neoclassical theorists assume infinite calculating power, behavioral theorists assume that human rationality is bounded (Simon, 1955) in various ways. However, neoclassical theorists often complain that behavioral theorists lack any coherent *theory* of irrationality to counter the elegance of traditional economic models. For many behavioral economists, the only theoretical game in town is Kahneman's

(2002) dual-process framework of System 1 and 2 processes that vary in their recruitment of intuitive versus deliberative processes—heuristics versus calculation. But this framework has a major shortcoming: It operates well in contexts of *risk* (where outcomes can be enumerated and probabilities assigned) but has little to say about contexts of *uncertainty* (where they cannot; Knight, 1921). Fundamentally, the economic world is riddled with uncertainty because the future has yet to be invented. Not only are conventional standards of rationality inapplicable in such situations, but dual-process theory gives us little guidance for how people make sense of the present to *imagine* the future (Beckert, 2016; Beckert & Bronk, 2018; Bronk, 2009). Given that many economic decisions depend on our beliefs about the future—for example, decisions about investment and business strategy—this problem sharply limits the relevance of existing behavioral theories for understanding economic activity.

Second, *the origin of booms and busts*. Macroeconomics has a wealth of theoretical tools for understanding business cycles *ex post*, but has been remarkably poor at predicting economic crises *ex ante*. Keynes (1936) famously invoked "animal spirits" in accounting for the mysteries of bubbles and crashes and some more recent theorists, such as Shiller (2000, 2017) and Tuckett (2011), have argued that macroeconomic (in)stability is driven largely by what narratives are circulating in a society. This cannot be understood without an understanding of both the psychology of narrative within individuals and the sociology of information propagation across individuals. Neither of these crucial areas are dealt with in neoclassical economics nor in black-box behavioral models.

Third, *voter psychology and economic policy*. The assumption that ordinary people are biased does not automatically imply that corrective government actions can do better, since government officials themselves are humans and therefore susceptible to incentives (Brennan & Buchanan, 1985) and cognitive bias (Jolls, Sunstein, & Thaler, 1998). Perhaps even more concerningly, since democracies adopt policies in response to the electorate, economic policy is dictated to some degree by the intuitions that ordinary people have about how markets work and what is therefore in their own or in the national interest (Caplan, 2007). Since economists, having taught their subject to ordinary humans, often lament the poor state of economics understanding, it seems widely agreed that voters' ordinary mental models of the economy are likely to be incomplete or biased in various ways. But surprisingly little has been done—within behavioral economics or any other branch of the social sciences—to understand how ordinary people make sense of economic activity. A sound understanding of this issue is critical to explaining why we get the public policies that we do.

Without claiming that cognitive science can solve any of these puzzles on its own, I argue that cognitive insights usefully supplement the analyses offered by neoclassical and existing behavioral approaches to all of these problems, alongside other social sciences such as sociology. In the end, I'll argue more broadly for cognitive science and its allies should be included in conversations with economics, as they help to enrich behavioral approaches that rely mainly on black-box modeling.

3 The Science of Sense-Making

Humans have a powerful drive to make sense of events (Chater & Loewenstein, 2016). In our everyday experience, we puzzle over one another's thoughts and motivations, we speculate about the hidden causes of daily news events, we imbue our lives with meaning. How we make sense of things often has important implications for economic activity as well. Stock analysts try to infer the reasons for changes in companies' financial performance, sales managers try to make sense of consumers' changes in demand, consumers evaluate whether marketing claims are credible, voters infer the effects of government policies on their paychecks, and executives build an understanding of their competitors' strategy to predict their behavior. Such issues are at the heart of fields such as finance (Barberis & Thaler, 2003; Shefrin, 2001), decision analysis (Bazerman & Moore, 2013), strategy (Powell, Lovallo, & Fox, 2011), public policy (Shafir, 2013; Viscusi & Gayer, 2015), and consumer behavior (East, Wright, & Vanhuele, 2013).

People seem to have at least three kinds of explanatory reasoning tools in their heads—*hypothesis-inference heuristics*, *narrative thinking*, and *intuitive theories*—serving different but overlapping functions. They apply, loosely, to thinking about *causal forks*, *causal chains*, and *causal webs*.

First, *causal forks*: A or B could cause X; which is it? People often wish to know what caused some particular event to happen, because knowing that cause gives them decision-relevant information or helps them to infer other important information. They use *hypothesis-inference heuristics* to do so.

Second, *causal chains*: A causes B, which causes C, which causes X; what could A, B, and C be? People often wish to stitch together long causal chains that can simultaneously account for past events while forecasting future events. They use *stories* to accomplish this.

Finally, *causal webs*: A, B, C, and D are causally related in some way; what causes what? People often need to form an understanding of how complex systems of variables influence one another. They build *intuitive theories* to understand these influences.

In the next sections, I review the key theoretical insights and empirical results that cognitive science has revealed thus far about these three sense-making tools, and examine ways that these insights can help us to understand economic phenomena.

4 Hypothesis-Inference Heuristics

Many cognitive processes can be understood as inferring which hypothesis best explains the available data (a process dubbed *abductive inference* by the philosopher Charles Peirce [1997/1903]). Vision allows us to infer which configuration of objects in the world best explains the two-dimensional light patterns hitting our retina; language understanding allows us to infer which meaning of a sentence best explains a sequence of sounds; memory allows us to infer which sequence of past events best explains the disparate traces of recollection rattling around our brains. Typically these processes are automatically executed by the brain without our even realizing we are assessing hypotheses at all. But other sense-making processes sometimes require more conscious effort, such as inferring what caused some event that we observed, which social category a person belongs to based on their traits, or what your friend is thinking based on their actions (e.g., Asch, 1987/1952; Dennett, 1987; Kelley, 1973). A theoretical framework called *explanatory logic* examines what these seemingly very different processes of hypothetical inference have in common, and what underlying cognitive processes they share (Johnson, 2018a). Any such processes would likely be important for understanding how we think and behave in economic contexts.

For instance, suppose Barbara, the CEO of a firm, observes that competing firm Acme Labs is buying up large quantities of tin. She wants to know why this is, given that only one of Acme's current products – the Model T widget – includes major tin components. It could be because Acme has expanding its production of T-widgets, which are also produced by Barbara's firm, or it could be because Acme is introducing a new tin-based product, which may or may not compete directly with Barbara's products. These two inferences have very different implications for Barbara as CEO. In the former case, she may need to take aggressive steps to head off Acme's widget play, perhaps through aggressive advertising, price promotions, or quality improvements. In the latter case, Barbara may want to know what new product Acme is introducing, perhaps looking to introduce her own version of this product or to re-position one of her existing products as a substitute for it. Explanations matter.

One approach, tailor-made for thinking through such problems, is Bayesian inference (Pearl, 1988). We assign initial degrees of belief to each hypothesis (*prior probabilities*) and update these initial beliefs in light of how well each hypothesis explains the evidence (*likelihoods*). If Barbara is a strict Bayesian, she would first consider, in the absence of knowing about the tin purchase, the relative odds that Acme would expand T-widget production versus introduce a new product. Let's say the former is twice as likely as the latter. Next, Barbara would evaluate the fit of each hypothesis to the evidence, that is, how likely the observed tin purchase would be given expanded production of T-widgets versus a new product. Let's say the tin purchase is enough to make a heck of a lot of T-widgets, so that it is somewhat implausible and the tin purchase is four times more plausible under the new-product hypothesis. Reverend Bayes gave Barbara a neat trick for computing which hypothesis is therefore likelier given the observed evidence—simply multiplying these two ratios (2/1 * 1/4 = 1/2). With this final step, Barbara concludes it is twice as likely the company is introducing a new product rather than expanding T-widget production and can plan accordingly.

In fact, some cognitive scientists believe that the great unifying process underlying the diverse cognitive processes mentioned above—perception, language understanding, causal reasoning, and so on—is precisely Bayesian inference (Lake et al., 2017; Tenenbaum et al., 2011). This may be surprising to many behavioral economists, used to siding with psychologists over neoclassical economists in the rationality wars, because this community of computational cognitive scientists essentially believe that human beings are rational, perhaps nearly optimal, information processors. Indeed, mathematical models of human behavior that assume Bayesian inference fit behavior well in a wide range of tasks, including how people learn the meaning of words (Xu & Tenenbaum, 2007), other people's goals (Baker, Saxe, & Tenenbaum, 2009), the masses of objects (Hamrick et al., 2016), the properties associated with categories (Tenenbaum, Griffiths, & Kemp, 2006), whether two variables are causally related (Griffiths & Tenenbaum, 2005), and how responsibility should be assigned for outcomes (Gerstenberg et al., 2018), among many other kinds of inferences.

However, there are good reasons to suspect that people do not have generalized Bayesian engines in their brains that optimally solve hypothesis-inference problems. It is true that people are remarkably close to optimal Bayesians for some kinds of tasks: People are highly adept at tasks such as perception that are “encapsulated” from conscious thought, and surprisingly skilled at many highly constrained tasks that require more explicit reasoning. But these tasks are not typical of many real-world problems that humans solve. Realistic hypothesis-inference problems pose at least four seemingly insuperable challenges, so daunting that no known algorithm can solve them with anywhere near human adeptness. These are the challenge of searching through a potentially infinite set of possible hypotheses (*hypothesis space limits*), the challenge of making inferences in situations where potentially critical information is unknown (*information limits*), the challenge of the imprecision of most of our knowledge (*specification limits*), and the challenge of exponential explosions in the computational complexity of apparently optimal reasoning strategies (*capacity limits*). Simply put, optimal Bayesian inference in all but the simplest cases is not merely difficult—it is impossible.

The question we must ask ourselves here is why humans are not bumbling around the planet with no clue what is going on. We are shockingly good at hypothesis-inference problems, despite these limitations. How is this possible? The answer is that humans use a suite of heuristics and strategies to circumvent these limits. Within cognitive science, there are two clashing notions of heuristics. The glass-half-empty “heuristics and biases” approach (Kahneman, 2011; Tversky & Kahneman, 1974) familiar to behavioral economists says that humans fall back on these short-cuts to reduce effort, largely out of cognitive laziness, and emphasizes the systematic biases associated with heuristic thinking. The glass-half-full “adaptive heuristics” approach (Gigerenzer & Goldstein, 1996) emphasizes the adaptiveness of heuristics relative to optimizing procedures such as linear regression, and argues that heuristics exploit the most relevant information while ignoring less critical information that can introduce overfitting. Some classical economists (e.g., Alchian, 1950) have taken a similar approach, arguing that although heuristics often lead to suboptimal choices, decision processes evolve over time to rely on heuristics that are successful and to avoid heuristics that are not (see Schlicht, 1998 for related discussion on the role of custom in economic behavior).

But at bottom, it seems clear that the glass is both half-empty *and* half-full. Heuristics *do* sometimes lead to systematic biases. And they usually *are* adaptive. This is because cognition without short-cuts is impossible (Chomsky, 1965; Keil, 1981). Most of the time, biased-but-reasonable inferences are better than no inferences at all, and we have a set of heuristics that work reasonably well for hypothesis-inference problems despite a distinct lack of optimality. This view is probably closest to the “resource rationality” view common among some proponents of Bayesian inference (Shenhav et al., 2017; see also Simon, 1955), which says that people do use biased heuristics to solve problems, but deploy these heuristics in a way that distributes cognitive resources efficiently given our sharp limits. This view seems to usefully reconcile Kahneman, Tversky, and Gigerenzer.

Now, let’s consider how heuristics circumvent each of the limits mentioned above.

First, *hypothesis space* limits reflect the fact that the world usually does not supply its own hypotheses, but we must instead create them. Barbara had to come up with the idea that her competitor might be expanding T-widget production or might be introducing a new product. But there are many other ideas that never occurred to her at all, despite their logical possibility. The

CEO of Acme could have accidentally ordered tin when he had instead meant to order aluminum; he could be doing a favor for his friend in the tin industry; he could be trying to corner the tin market in the tradition of the Hunt brothers; he might believe in numerology and admire tin's atomic number 50. But she did not think of these bad hypotheses and then take the effort to reject them; she just thought of the plausible ones. According to one view, we choose which hypotheses to consider by sampling the space of possible hypotheses according to their prior probability (e.g., Dasgupta, Schulz, & Gershman, 2017). But this begs the question of both how the hypothesis space itself is constructed and how prior probabilities are assigned to each hypothesis; even if true, this can only be a partial explanation. Several research programs have studied inductive biases that lead people toward certain kinds of hypotheses (Kalish, Griffiths, & Lewandowsky, 2007; Lagnado et al., 2007). For instance, people rely on knowledge of stable causal mechanisms (Johnson & Ahn, 2015, 2017), the accessibility of information in memory (Hussak & Cimpian, 2018), and the structure of events across time (Derringer & Rottman, 2018; Johnson & Keil, 2014; Lagnado & Sloman, 2006) as useful cues to generating hypotheses. We will see later on that thinking through stories can also prune the hypothesis space.

Second, *information limits* exist because the available data often underdetermines which hypothesis is correct. The CEO would love a peek inside her competitor's factory to test these hypotheses, but cannot do so without committing industrial espionage. People have an impressive capacity to generate evidence by marshalling other relevant information from memory and considering its implications (e.g., recalling a presentation from members of the engineering team who had mentioned possible advantages of tin components, conditional on other technological breakthroughs, and inferring that the competitor may have experienced such a breakthrough). Less impressively, people tend to infer evidence even where none exists by using irrelevant cues, and this often leads people to make erroneous inferences about hypotheses that make unverified predictions (Johnson, Rajeev-Kumar, & Keil, 2016; Khemlani, Sussman, & Oppenheimer, 2011).

Third, *specification limits* exist because Bayesian methods for evaluating hypotheses require precise numerical probabilities, which hypotheses typically do not wear on their sleeves—that is, we often operate in an environment of Knightian uncertainty. In the numerical example above, Barbara was able to estimate the prior probabilities of the widget-expansion hypothesis over the new-product hypothesis as 2-to-1, and the likelihood of the data as 1-to-4 under these two hypotheses. How did Barbara come up with such figures and why don't they have more decimal places? What database could Barbara have consulted, for instance, to calculate the prior probability that the competitor would expand widget production? One strategy people use for circumventing this problem is to use Occam's razor to infer simpler rather than more complex hypotheses, since simpler hypotheses tend to have higher prior probabilities, balancing this factor against the fact that more complex explanations often are better able to fit the data (Johnson, Valenti, & Keil, 2019; Lombrozo, 2007). This strategy, unlike Bayesian inference, need not be accompanied by precise probabilities, but nonetheless can flexibly address hypothesis-inference problems by weighting simplicity differentially across contexts.

Fourth, we face *capacity limits* if we try to use uncertain inferences about hypotheses to make further predictions. Suppose Barbara goes ahead and calculates a 70% probability that the competitor is introducing a new product. This fact is not itself what Barbara wants to know. Instead, she would like to know how this will affect her own market position. If Acme is introducing a new product, is it in a competing market? If so, which one and how much will this weaken Barbara's firm's position? If not, which one and can Barbara's firm enter that market to compete on price or quality? If Barbara's firm entered the new market, how long would it take to recoup this investment and would it have positive net present value? Each of these questions depends on the answers to the previous ones, and each possible answer raises new questions. Making optimal predictions from uncertain hypothetical inferences requires us to keep track of the uncertainty at each stage and propagate it across the chain of inferences—a task that compounds exponentially in computational complexity with the number of steps. People use a grossly simplifying heuristic to solve such problems, called *digitizing*—rather than treating probabilities as analog quantities between 0 and 1, they often treat them digitally, as though either 0 or 1, when making predictions (Johnson, Merchant, & Keil, in press; Murphy & Ross, 1994; Steiger & Gettys, 1972). This means that people systematically ignore uncertainty and focus on a single predictive pathway to the exclusion of others. On the plus side, this allows us to use hypothetical inferences to make predictions. On the minus side, these predictions are systematically overconfident in the sense that they are too close to 0 or 1. This sort of dynamic may contribute to boom-and-bust cycles in the macroeconomy, for instance when homeowners and investors ignore the low but non-zero probability that their homes values will decline (Gennaioli, Shleifer, & Vishny, 2015).

Digitization may also help to explain the excessive volatility found in stock prices (Shiller, 1981). For example, stock market futures performed a strange dance on the night of Donald Trump's election in November 2016. As the exit polls increasingly came to favor Trump over Clinton, S&P 500 futures sank in value, nearly 4% in a few hours. In the early hours of the morning, futures prices began to rise as steadily as they had sank, coinciding with Trump's uncharacteristically gracious victory speech as Clinton conceded the race. Futures prices rose as fast as they had sank, and by the time trading opened the next morning the price had recovered to the level of the previous evening's close. The *Wall Street Journal* explained this event as the market's oscillation between adopting a "Bad Trump" hypothesis (protectionist, unpredictable) versus a "Good Trump" hypothesis (tax-reforming, regulation-slashing). Perhaps if we knew with certainty which Trump would govern, this really could explain 4% of the present-discounted future dividends of American companies. But this market swing was evidently based on almost no information—a speech which provided little in the way of policy but which managed to avoid protectionist rhetoric. This might raise our credence in Good Trump from 45% to 55%, but surely not from 0% to 100%. Unless, of course, the stock market in aggregate tends to digitize, "rounding up" probabilities like 55% closer to 100% and "rounding down" probabilities like 45% closer to 0%. We will never know what investors were thinking that night, but experimental evidence shows that in general, lay (and possibly even professional) investors appear to reason about stock prices just this way (Johnson & Hill, 2017).

Overall, hypothesis-inference problems are widespread both in everyday cognition and in economic decision-making. These problems, posed abstractly, could be solved effectively by Bayesian calculations, but these calculations, when even modest elements of realism are introduced, prove practically and even conceptually impossible. Humans have accumulated heuristics to circumvent these inherent limitations, and while these heuristics do introduce (sometimes systematic) errors, they perform well enough in real-world settings to allow humans to get by. A growing experimental literature finds that these heuristics emerge early in childhood (Bonawitz & Lombrozo, 2012; Johnston et al., 2017) and that these same heuristics guide basic cognitive processes such as causal thinking (Johnson, Rajeev-Kumar, & Keil, 2016; Khemlani et al., 2011; Lombrozo, 2007), category-based reasoning (Johnson, Merchant, & Keil, 2015; Murphy & Ross, 1994; Sussman, Khemlani, & Oppenheimer, 2014), and visual tasks (Johnson, Jin, & Keil, 2014), as well as intuitions in applied settings such as stereotyping (Johnson, Kim, & Keil, 2016), consumer choice (Johnson, Zhang, & Keil, 2016), and finance (Johnson & Hill, 2017).

Hypothesis-inference heuristics likely lie at the heart of the solution to the first puzzle raised earlier—how people can make decisions at all in an environment of Knightian uncertainty, given that nature often wears neither hypotheses nor their associated probabilities on its sleeves: Possibilities must instead be imagined. Although I referred to some of these problem-solving tactics as “heuristics,” which would typically be associated with automatic System 1 processing, it’s not clear how well these hypothesis-inference heuristics fit in with a dual-process framework. Sense-making is fundamentally about active processing of information and about modeling possibilities in one’s mind. Although many aspects of these processes are surely executed outside of awareness, it seems that deliberative processes are likely to prevail in many cases. Such cases where automatic and deliberative processes are interleaved may indeed be the norm rather than the exception in cognition.

5 Stories

A second tool that people use is narrative thinking—the process of taking a sequence of events, imposing a causal and temporal order on it (a story), and using that story to predict what will happen next. This is related to, but distinct from, the hypothesis-inference problems I described above. Those problems typically revolve around identifying a causal hypothesis that explains some data, with knowledge of that cause in turn being useful for action directly or for making a prediction about some other thing it affects. Stories are richer than this. They are chains of causation with a distinct temporal order, with goal-directed activity at their center, and which by their nature predict events yet-to-come in that causal–temporal chain.

The role of stories in decision-making (Pennington & Hastie, 1992) and economic activity (Akerlof & Snower, 2016; Beckert, 2016; Holmes, 2014; Shiller, 2017) has been increasingly acknowledged in recent years. David Tuckett has proposed *conviction narrative theory* (CNT) as a sociological and psychological theory of how humans use narratives to think, decide, and communicate (Tuckett, 2011; Tuckett & Nikolic, 2017). Tuckett identifies several functions of narratives in economic decision-making—making sense of situations in order to identify opportunities; simulating the consequences of potential actions; communicating the rationales underlying choices to gain social support; and maintaining conviction for a chosen action in the face of uncertainty (see Akerlof & Snower, 2016; Mercier & Sperber, 2018).

As just one example of stories in economics, narrative thinking appears to play an outsized role in how the world’s investment capital is allocated across equities. Tuckett (2011) interviewed dozens of fund managers, collectively responsible for managing over $500 billion. These interviews uncovered numerous examples where managers used stories for all these purposes: To spot opportunities (e.g., situations in which market prejudice led a company to be undervalued), to imagine what would happen if they acted (e.g., predicting the price will revert to reflect fundamentals after a delay), to justify these choices to others (e.g., investors or subordinates), and to maintain conviction (e.g., to hold onto a stock after a decrease in its price). This last function—maintenance of conviction—is analogous to the "belief digitization" results described above. That is, the managers consider multiple possible stories, and adopting the one they consider likeliest rather than trying to integrate across the probabilities of all the different stories when they act (if indeed these probabilities were even calculable in any meaningful way). This is probably crucial for avoiding paralysis in the face of profound uncertainty.

Ongoing experimental work has been examining the cognitive underpinnings of narrative thinking, as well as its consequences for financial decision-making. This work has supported a number of insights broadly consistent with the more qualitative research mentioned above. Three broad conclusions can be reached on the basis of this work.

First, *people automatically supply stories when using data to form expectations*. One study focused on how investors use explanatory information (e.g., from analysts) in predicting prices. Participants read about companies whose stock price had either increased or decreased (Johnson, Matiashvili, & Tuckett, 2018a). When these price changes were explained as occurring due to an internal cause (e.g., poor management), participants were more likely to extrapolate the trend into the future, compared to when the explanation invoked an external cause (e.g., a supply shock). This is consistent with the idea that internal causes would be perceived as more stable over time. However, either type of explanation led people to extrapolate trends more compared to a condition in which no explanation was given. In a follow-up study, even unexplained price trends were treated more like signal than like noise, particularly price increases. Such beliefs could potentially lead to stock prices that are rigid downwards, because price decreases require more evidence to be perceived as "real" compared to increases.

A related study looked at how investors use price history information in predicting prices. There is evidence that investors tend, by default, to extrapolate past trends linearly, such that recent price increases are expected to give way to future price increases, and vice versa (De Bondt, 1993). But recent research has found that people actually reason about price trends in a more sophisticated way that relies on pattern-matching (Johnson, Matiashvili, & Tuckett, 2018b). Although people do assume that linear price changes will be followed by further price changes in the same direction, people are much less likely to extrapolate trends when the price history includes previous periods of reversion (the price both increased and decreased) or a period of stability (the price held constant at one level). This was true for a variety of different prices in addition to stock prices (e.g., foreign exchange rates, futures contracts, consumer goods), occurred under incentive-compatible conditions, and, like the effect of attributions described above, was observed among finance experts. Such pattern-based expectations should be accounted for in models of investor behavior, as they can in principle lead to feedback loops among price changes, price expectations, and investing behavior.

Second, *narrative-based expectations produce downstream consequences for other thoughts and behaviors*. For example, one study looked at how participants use company news to predict the company's future stock price (Johnson & Tuckett, 2017). Participants predicted future prices in light of a positive or negative piece of news about a company (e.g., positive or negative earnings surprise) which was either about the future or the past (e.g., last quarter's actual earnings or next quarter's predicted earnings). Mainstream financial theory (Fama, 1970) says that such information should have no impact on stock prices, assuming some gap between the time when the announcement was made and when we learn about it (so that the market prices in the information). So if people follow rational expectations, positive or negative news should be treated similarly. A second possibility, motivated by behavioral finance, is that people would instead predict stock prices in a way consistent with known econometric trends (Bernard, 1992), namely that stocks have short-term momentum (prices overreact relative to the long-term trend) followed by mean-reversion in the longer-term (reverting to the original trend).

But in fact, participants followed a third model—their expectations became increasingly extreme at longer time horizons, such that they predicted a modest difference in stock prices between positive versus negative news at a 2-week interval, but much larger differences at a 1-year interval. This is inconsistent with both rational expectations (there should be no difference at any time horizon) and also standard behavioral accounts (there should be a larger difference at a short time horizon and smaller difference at a longer time horizon). Instead, participants appeared to rely on narrative thinking, inferring some underlying cause that will lead to stable price increases or decreases into the future. Moreover, this trend was exacerbated by news that was future- rather than past-oriented, consistent with the idea that narrative thinking involves an important temporal component. Similar results were observed for a group of participants highly knowledgeable about investing (e.g., PhD students in economics, MSc students in finance, and professional financial analysts).

In addition to confirming again the role of narrative thinking in expectations, this study looked at how these expectations influence choices and the emotional dynamics mediating this process. These beliefs about future trends indeed translated into decisions—participants were more likely to include stocks in a hypothetical portfolio when those stocks had more positive future expectations, and this was true even though standard financial advice would give very different advice, both under efficient markets assumptions (Malkiel, 2015) and under behavioral assumptions (Jegadeesh & Titman, 1993). These choices were in turn mediated by emotional processing, which is an integral part of narrative-based choice according to conviction narrative theory (see Damasio, 2006). Participants' choices to include a security were accompanied by a prevalence of positive, approach emotions over negative, avoidance emotions. An economic role for emotion is also confirmed by large-scale econometric analyses of news databases, finding that the prevalence of excitement- versus anxiety-related words in the financial press predict macroeconomic aggregates such as GDP and output (Nyman et al., 2018).

Finally, *people attend carefully to trusted sources to inform their expectations and choices*. Indeed, endorsement from trusted sources can even override direct evidence (Johnson, Rodrigues, & Tuckett, 2018a). In one study, participants decided which stocks they wanted to include in a portfolio, where each stock was accompanied by information about its industry as well as conflicting opinions by two expert stock analysts. The companies' industries could be either prototypically associated with politically left (e.g., electric cars) or right (e.g., oil companies) sensibilities, and were endorsed by stock analysts with either more left- or right-leaning ideological views. The alignment between the experts' and participants' political views strongly predicted portfolio allocation choices, and completely swamped any effect of the companies' industries. That is, politically left participants would eagerly invest in oil companies if endorsed by a liberal analyst, and politically right participants would seize on the opportunity to invest in electric cars if endorsed by a conservative analyst. Source information is equally critical in guiding consumers' decisions about products, including cultural products such as books as well as seemingly apolitical products such as blenders (Johnson, Rodrigues, & Tuckett, 2018b). Thus, stories are likeliest to be adopted when they come from a trusted source. Since stories are bundled in a digestible form for communication, these trust dynamics likely govern their spread through social networks.

Although this work focuses mainly on financial decision-making, it is likely that analogous principles characterize behavior in a variety of other economic contexts, such as managerial strategy and consumer choice. In our earlier example, we considered a CEO deciding among competing explanations for her competitor's behavior. One of the major problems she faced was determining which hypotheses to even consider. This problem may be simplified through narrative thinking. For example, prototypical patterns of events—such as scripts (Schank & Abelson, 1977), schemas (Rumelhart, 1980), or causal mechanisms (Johnson & Ahn, 2017)—may be identified as skeletons, to which recent evidence can be added to flesh out a story. These complex stories may then, in turn, be evaluated based in part on the same hypothesis-inference heuristics used to evaluate simpler hypotheses, and then to form expectations along the lines of the studies of financial decision-making just described. Such hybrid patterns of thought may be ubiquitous in characterizing complex, real-world decisions such as strategic choices. Such reasoning strategies are difficult to study experimentally because they contain a multitude of moving parts; but such study will be increasingly important as we try to marry cognitive science with real-world economic choice.

Overall, stories and their associated cognition and sociology are likely to be part of the solution to the second puzzle raised above—why financial markets can be stable at times and unstable at others (see also Meder, Le Lec, & Osman, 2013). Because people tend to adopt a single narrative at a time, the gradual accumulation of evidence may have modest effects on an individual investor's sentiment as long as that narrative can be maintained—narratives permit conviction in the face of uncertainty (Tuckett, & Nikolic, 2017). This is probably adaptive for individuals most of the time, in part because conviction supported by narratives discourages investors from over-trading. Indeed, narrative thinking on the part of individual investors may even be conducive to market stability, as swings in investor sentiment can be dampened that might otherwise lead to stampede dynamics—narratives help us to coordinate. But shared narratives can also lead to bubbles as a socially shared narrative comes to dominate a market and the story takes on its own reality—and, when enough investors reach a tipping point, to panic and crash (Shiller, 2000; Tuckett, Smith, & Nyman, 2014). Taking account of the cognitive and social dynamics by which people use stories to shape their expectations appears to be an important direction for macroeconomic modeling.

6 Intuitive Theories

Hypothesis-inference heuristics and stories are useful for understanding an individual event, acting on it, and predicting the future. But humans often wish to go beyond individual experiences and form more generalized knowledge. Several interconnected literatures in developmental psychology examine the intuitive theories that children have of how the physical, biological, and social worlds work. The astonishing result of this decades-long research tradition is that children, even infants, have remarkably rich understandings of these domains (Spelke, 2000). Babies understand, for example, that unsupported objects fall down (Needham & Baillargeon, 1993), that one plus one equals two (Wynn, 1992), that living things have solid insides (Setoh et al., 2013), and that people will act on false beliefs rather than unknown truths (Onishi & Baillargeon, 2005). It is reasonably clear why natural selection would have built such intuitions into our minds—even primates share some of our intuitions about physics (Santos & Hauser, 2002), and given humans' ecological niche it makes sense that we have uniquely well-tuned instincts about the social world (Frith & Frith, 2007).

But in recent millennia, human culture has advanced exponentially faster than biological evolution, and society has given us fantastically sophisticated technological tools and social institutions (Boyd, Richerson, & Henrich, 2011). But this is a story of collective success in the face of widespread individual failure (Sloman & Fernbach, 2017). Despite the illusion that we understand how complex artifacts such as locks or toilets work, most individuals have amazingly shallow knowledge about their underlying causal mechanisms (Rozenblit & Keil, 2002). Our ability to piece together sophisticated intuitive theories is remarkably poor for domains where biological evolution has not prepared us. Yet, the cultural evolution of technology can be considered a triumphant success because it is usually unimportant for people to know how the gadgets around them work, so long as they can use them.

But it is not all triumph. In a market economy, and a democratic one especially, it is important for people to understand how socially agreed institutions work. Humans, as Adam Smith wrote, are not pieces on a chessboard to be pushed around at will, but "in the great chess-board of human society, every single piece has a principle of motion of its own" (Smith, 1759). Institutions, then, exist in a feedback loop among our individual human nature as market participants, the emergent forces that govern the economy within a particular set of institutions, and the beliefs and choices we make within those institutions to shape them. Our knowledge of economic institutions can affect our behavior as market participants, and as voters our ignorance can damage or destroy those institutions.

This topic has received some attention in political economy. For example, Bryan Caplan (2007) argued that voters' systematic deviations from economists' views constitutes a serious obstacle to effective democracy. He compared economists' versus laypeople's answers to the same questions (Caplan, 2002), and identified four biases suffered by laypeople relative to economists—make-work bias (conflating economic growth and employment), anti-foreign bias (dismissing the benefits of interacting with foreigners), pessimistic bias (unduly negative perceptions of current economic conditions and their improvement relative to the past), and anti-market bias or emporiophobia (distrusting market mechanisms; see Rubin, 2014). While the evidence for these biases is compelling and their political effects undeniable, Caplan's analysis does little more than to supply labels for them—a deeper analysis would probe why people hold these systematic misconceptions and whether there is potential to correct them. This is precisely the kind of work cognitive scientists do.

Until recently, cognitive scientists paid little attention to our intuitive economic theories. However, an explosion of interest promises to accelerate our understanding greatly (Boyer &

Petersen, 2018; Leiser & Shemesh, 2018). This emerging research tradition has probed laypeople's mental models of a wide range of economic phenomena, though the research on any one topic is typically very thin. This includes basic economic concepts such as supply and demand (Leiser & Halachmi, 2006), marginal utility (Greene & Baron, 2001), exchange (Cosmides & Tooby, 1992; Fiske, 1992), optimal decision-making (Jara-Ettinger et al., 2016; Johnson & Rips, 2014, 2015); trade-offs (Fiske & Tetlock, 1997), profit (Bhattacharjee, Dana, & Baron, 2017), and property (Blake & Harris, 2009; DeScioli & Karpoff, 2015; Friedman, 2010); major economic phenomena including inflation (Leiser & Drori, 2005), unemployment (Furnham, 1982), inequality (Gandy & Baron, 1998; Starmans, Sheskin, & Bloom, 2017), poverty (Furnham, 1982), and financial crises (Leiser, Bourgeois-Gironde, & Benita, 2010); and policy issues such as taxation (McCaffery & Baron, 2003, 2006), public goods (Kemp, 2002), redistribution (McCaffery & Baron, 2005; Petersen et al., 2012; Skitka & Tetlock, 1993), regulation (Haferkamp et al., 2009; Hirshleifer, 2008), immigration (Hainmuller & Hiscox, 2010), and international trade (Baron & Kemp, 2004; Hiscox, 2006; Kemp, 2007). Further, a tiny but fascinating literature looks at how people believe these concepts relate to one another, particularly in macroeconomics (Leiser & Aroch, 2009; Williamson & Wearing, 1996).

Although the literature on each of these topics is individually thin, one major and consistent finding is that people construe these issues in moral terms to a much greater degree than economists (Coase, 1960 is a classic example), consistent with standard behavioral economics results documenting attitudes toward price fairness that are quite foreign to economists' analytical toolkit (Kahneman, Knetsch, & Thaler, 1986). This supports Rubin's (2003) contention that folk economic thinking focuses almost exclusively on the distribution of wealth rather than its creation. Indeed, moral concepts even appear to creep into views of macroeconomic causation, which are dominated by the notion that "good begets good" (Leiser & Aroch, 2009), such that "bad" economic phenomena are causally related (e.g., unemployment and inflation) and inversely related to "good" phenomena (e.g., growth). Macroeconomists disagree on much, but saltwater and freshwater alike can agree that this is nonsense. Yet, if inflation expectations are a key driver of inflation itself (Friedman, 1968; Solow, 1969), such nonsensical beliefs can become self-fulfilling prophecies.

Let's zoom in on one of these issues to better understand the sorts of fruits this research can offer. Rubin (2003) suggests that one of the deep differences between economists' versus laypeople's mental models of economic activity is that economists view most transactions as positive-sum, whereas laypeople view them as zero-sum (explaining, incidentally, why lay economic theories prioritize distribution above production). There has been surprisingly little empirical attention paid to the possibility that people have a zero-sum mental model of economic transactions, though zero-sum beliefs have been found in other domains (Burleigh, Rubel, & Meegan, 2017; Meegan, 2010; Newman, Gorlin, & Dhar, 2014; Pilditch, Fenton, & Lagnado, 2019; Rozycka-Train, Boski, & Wojciszke, 2015; Smithson & Shou, 2016). However, it seems intuitive that people would think in this way, is consistent with a good deal of political rhetoric, and would help to explain some of the biases Caplan (2007) identified, such as anti-foreign bias (see also Bazerman, Baron, & Shonk, 2001). Does zero-sum thinking in fact explain protectionist attitudes in trade policy, and if so, what cognitive factors lead people to think in this way?

Taking the latter question first, experimental studies have demonstrated that there are at least two principal drivers of zero-sum thinking. A first reason is people's tendency toward intuitive mercantilism (cf. Smith, 1776). Mercantilism is, of course, the pre-Smithian notion that wealth should be identified with money rather than with useful goods and services. One series of experiments tested this idea by describing extremely simple, everyday economic transactions to research participants (Johnson, Zhang, & Keil, 2018a), such as Sally buying a $30 shirt from Tony's store, Eric getting a $15 haircut from Paul's barber shop, or Vivian and Tommy swapping their McDonald's and Burger King hamburgers. Economics, along with Smithian common sense, tells us that for the monetary transactions, the buyer and seller both benefit, since they otherwise would not have agreed to the transaction, and likewise both barter partners must be benefitting or they would not have traded. But laypeople do not share these intuitions. They believe that sellers benefit at buyers' expense, while neither trader benefits from a barter. This is bizarre in a Smithian world, but not in a mercantilist one where the notion of benefit is restricted to monetary benefit. Buyers do indeed lose money (though they value it less than what they buy) while sellers gain money (which they value more than what they sell), while no money is exchanged at all in a barter.

(The second reason for zero-sum thinking, less relevant perhaps to international trade, is that people often fail in spontaneous perspective-taking (Lin, Keysar, & Epley, 2010). Smith teaches us that "it is not from the benevolence of the butcher, the brewer, or the baker, that we can expect our dinner," but equally it is not from the buyer's benevolence that they purchase their dinner. Such insights require us to take the perspective of the buyer and seller to recognize their own motivations, and failing at this can exacerbate the zero-sum thinking produced by mercantilism. This is supported by experimental evidence. In experiments similar to those described above, giving explanations for the buyers' actions—even empty ones ("Sally made the purchase because she wanted the shirt")—greatly reduced the rate of zero-sum thinking.)

If people extend these zero-sum beliefs about sellers (exporting countries) "winning" at the expense of buyers (importing countries), then precisely the same logic underwriting zero-sum beliefs about individual transactions would produce anti-trade attitudes in the context of the global economy. Once again, this is confirmed by multiple lines of converging experimental evidence (Johnson, Zhang, & Keil, 2018b). First, beliefs about importing and exporting countries precisely mirror those about individual buyers and sellers, with exporting countries as "winning" and importing countries as "losing." For example, if participants are told that "Some people, who live in the United States, order pairs of Nike running shoes from Thailand. They each pay $150 for the shoes and receive them in the mail," participants tend to believe that the U.S. is made worse-off while Thailand is made better-off. Second, these beliefs even extend to domestic trade—states that import goods from other states are seen as "losing" at the other states' expense—although these intuitions are less strong than country-level intuitions. Finally, these effects can be largely undone by invoking the concept of balance of payments (going back to Smith's friend and intellectual fellow-traveler David Hume, 1752). That is, dollars in must equal dollars out as a matter of accounting, so that dollars paid for imports must return from exports or investment (e.g., purchasing U.S. debt). When this concept is made salient (e.g., "The sellers of the shoes used the dollars they received to purchase U.S. products and invest in the U.S. economy"), imports are deemed much less harmful. This is good news from the standpoint of challenging erroneous views, but additionally it is strong support for the notion of intuitive mercantilism—such arguments undercut trade-skepticism by highlighting the fact that even mercantilist views (identifying wealth with money) imply that trade can be neutral as long as the money ultimately comes back home one way or another.

This explanation of trade-aversion in terms of intuitive mercantilism differs from several others on offer for why people are averse to international trade. Although these alternative explanations are not mutually exclusive—there is indeed evidence for all of them—none are conceptually or empirically equipped to dispel intuitive mercantilism as the main driver of trade aversion (Johnson, 2018b).

First, as noted previously, humans and even some non-human animals have evolved intuitions about physics, and humans may also have evolved intuitions about exchange (Cosmides & Tooby, 1992; Pinker, 2002). But such intuitions would have evolved in an environment of hunting, gathering, and barter among small bands, not a globalized economy intermediated by money. Consequently we may have strong but erroneous intuitions about the economy. Although this does explain why we do not have accurate evolved intuitions about trade, it does not explain why we have the specific erroneous intuitions we do. Our ancestors presumably would ridicule exporting countries for giving up valuable resources in exchange for useless bits of paper, not admonish them for exploitation.

Second, people may fail to understand the concept of comparative advantage (Baron & Kemp, 2004). Indeed, those with poor measured understanding of comparative advantage are more likely to favor trade restrictions. Interestingly, New Zealand participants tended to outperform Americans, possibly because living on a small island makes one's comparative disadvantages more salient.

Third, humans have strong evolved intuitions about supporting their in-group or tribe while battling their out-group or competing tribes (Boyer & Petersen, 2018). On this view, trade is aversive because it involves transferring resources to the out-group, even though one's own group also gains. This predicts that only international trade would be seen as aversive, whereas we have seen that even domestic trade (across states) and exchanges between individual consumers and retailers are seen as zero-sum. However, since zero-sum tendencies are indeed stronger for international trade, it is likely that coalitional thinking exacerbates existing mercantilist tendencies.

Like so many other economic issues, people thinking about trade appear to focus on distribution (allocating the pie) rather than efficiency (expanding the pie). And once again, this results in moralistic attitudes creeping into economic thinking. In experiments, people not only claim that imports are economically harmful, but that the consumers who choose to import these goods are behaving immorally. This is particularly true for imports from developing countries, which appear to trigger the paradoxical belief among some people that such trades are lose–lose. These moralistic attitudes are worrying for at least two reasons. First, they could very well drive public policy, both because politicians may hold similar attitudes, which may be further exacerbated through their selection by voters, and because voters may enforce them even among politicians who do not privately agree with them. Second, even in a regime of unfettered free trade, consumers who incorporate a moral cost into purchases of foreign goods may, at the margin, be less inclined to purchase foreign products even if foreign production is economically efficient. The price system leads to efficient outcomes because it coordinates the behavior of producers and consumers. If consumers experience an intangible, and economically illusory, moral cost to purchasing foreign products, international trade may be less efficiency-enhancing in practice than it appears on paper.

The cognitive underpinnings of economic intuitions have been studied most thoroughly for trade, in part because it is topical and politically contentious. But numerous other critical issues loom large, including policy issues such as taxation, regulation, and macroeconomic policy, and a full picture of economic activity must embrace the feedback loops between ordinary economic processes and the internal conceptions of these processes by economic agents. If we are to understand why voters often embrace poor economic policies, we will need a much fuller picture about how voters believe the economy works.

7 Toward a Cognitive Science of Markets

Humans are strikingly motivated to make sense of their world. This curiosity and capacity for actively processing information likely plays profound roles in both why markets are possible at all—the design of institutions, our ability to coordinate, investors' maintenance of conviction in the face of uncertainty—but these same processes can also contribute to inefficiencies or worse, such as boom-and-bust cycles and destructive economic policies. This is not to say that classic macroeconomic factors and incentive problems do not contribute to financial crises or that standard public choice mechanisms do not explain many public policy problems. They surely do. But these explanations are far from complete. They do little to explain the social dynamics that contribute to bubbles or the appeal of policies that are decidedly outside of voters' self-interest. For that, we need cognitive science.

Broadly, I see five reasons why we need cognitive science to enrich behavioral economics. First, as I noted above, behavioral economics has a behaviorist/positivist streak that it inherited from neoclassical economics—a singular focus on observable behavioral outcomes to the exclusion of internal states. Although it of course makes sense for economics to model behavior, a model *only* of behavior will tend to yield impoverished explanations and inaccurate predictions—for this reason, psychology gave up on the behaviorist project of ignoring internal states in the 1960s. Second, cognitive science acknowledges the richness of human nature and the multiplicity of motivations that drive human behavior. Although behavioral economics has enriched traditional models to include social utility, much more needs to be done to build a full conception of human preference. Third, neoclassical and behavioral models alike have difficulty explaining some cases where markets *succeed* rather than fail, such as our remarkable ability to coordinate and the powerful role of social norms in reducing transaction costs. Cognitive science, conversely, gives equal air-time to the mind's successes and failures and may therefore provide some clues into both successes and failures in markets. Fourth, cognitive science is intellectually pluralistic, embracing contributions across different fields (such as philosophy, artificial intelligence, and neuroscience) and methodologies (including case studies, interviews, surveys, experiments, and philosophical analysis). Both economics and psychology, in contrast, tend to be more closed-tent disciplines and can learn from cognitive science's promiscuous example. Finally, although every field has blind spots, the blind spots tend to differ. Economics has paid fairly little attention, for instance, to decisions under uncertainty as opposed to risk, but cognitive science, being somewhat less obsessed with probabilistic modeling, has been less blind to this issue. My own view is that cognitive science and economics have much to learn from one another.

I've discussed here how the cognitive science of sense-making can contribute to economics, in part because I think there is particularly low-hanging fruit here. But many other areas of cognitive science can be profitably integrated into economics. The literature on learning can be a critical addition to areas of behavioral economics that seek to characterize how behavior changes with experience, such as in behavioral game theory (Camerer, 1997). The literature on motivation not only points out a variety of drives not encompassed by rational choice theory (e.g., Ariely & Loewenstein, 2006), but proposes alternative unifying theories of motivation that might be profitably studied in economic contexts (Eccles & Wigfield, 2002). The literature on emotion tends to undercut the dominant view of emotion in behavioral economics as a biasing factor, instead identifying it as an integral part of ordinary human decision-making, mediating between goals and action (Damasio, 2006).

One particularly promising area is in social cognition and moral psychology—fields which have been advancing at breakneck speeds in the past decade. For example, one promising approach argues that humans are hard-wired intuitively for cooperation, but can override these intuitions and behave selfishly if the motivation and cognitive resources are available (Rand et al., 2014). Another new approach argues that people bargain "virtually"—that is, that humans solve coordination problems nonverbally by imagining what solution would emerge if verbal bargaining were possible (Misyak et al., 2014). And a variety of researchers have looked at specific moral intuitions that people hold, including many we may not consider entirely rational upon reflection (e.g., De Freitas & Johnson, 2018; Sunstein, 2005), which can inform demand-side behavior and create supply-side responses.

I am optimistic for the prospects of a *cognitive science of markets*—an interdisciplinary approach to economic activity that acknowledges the complexity of mental activity, the sophistication of market participants, and the emergent and often nonobvious outcomes that can emerge when many individuals—each eager to understand their world—make decisions together.

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