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Conviction Narrative Theory:

A Theory of Choice Under Radical Uncertainty

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Short Abstract

Conviction Narrative Theory (CNT) is a theory of choice under *radical uncertainty*—contexts where probabilities cannot be assigned to outcomes. CNT proposes that people use *narratives*—structured causal hypotheses—to make sense of data and make decisions. According to CNT, narratives arise from the interplay between individual cognition and the social environment, with reasoners adopting a narrative that feels 'right' to explain the available data; using that narrative to imagine plausible futures; and affectively evaluating those imagined futures to make a choice. We review evidence from many disciplines supporting this basic model, including lab experiments, interview studies, and econometric analyses.

Long Abstract

Conviction Narrative Theory (CNT) is a theory of choice under *radical uncertainty*—situations where outcomes cannot be enumerated and probabilities cannot be assigned. Whereas most theories of choice assume that people rely on (potentially biased) probabilistic judgments, such theories cannot account for adaptive decision-making when probabilities cannot be assigned. CNT proposes that people use *narratives*—structured representations of causal, temporal, analogical, and valence relationships—rather than probabilities, as the currency of thought that unifies our sense-making and decision-making faculties. According to CNT, narratives arise from the interplay between individual cognition and the social environment, with reasoners adopting a narrative that feels 'right' to explain the available data; using that narrative to imagine plausible futures; and affectively evaluating those imagined futures to make a choice. Evidence from many areas of the cognitive, behavioral, and social sciences supports this basic model, including lab experiments, interview studies, and econometric analyses. We propose 12 principles to explain how the mental representations (narratives) interact with four inter-related processes (explanation, simulation, affective evaluation, communication), examining the theoretical and empirical basis for each. We conclude by discussing how CNT can provide a common vocabulary for researchers studying everyday choices across areas of the decision sciences.

Keywords: Behavioral Economics; Causal Thinking; Cognitive Science; Decision-making; Emotion; Explanations; Imagination; Narratives; Reasoning; Social Learning; Uncertainty

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A Theory of Choice Under Radical Uncertainty

> "Before the wheel was invented… no one could talk about the probability of the invention of the wheel, and afterwards there was no uncertainty to discuss…. To identify a probability of inventing the wheel is to invent the wheel."
>
> – John Kay and Mervyn King, *Radical Uncertainty* (2020)

1. Everyday Decisions

A government amidst a public health lockdown debates exit strategy; a couple debates divorce. A university graduate considers her career options; the CEO of a toaster company considers expanding into blenders. A widow, awoken by a strange sound, contemplates whether to investigate its source; a burglar, outside, contemplates whether he is making a grave mistake.

We make such decisions, grand and petite, every day. This is remarkable because many everyday choices require us to solve six challenges—each daunting, together herculean:

- **Radical uncertainty.** *Our knowledge about the future often eludes quantification*. (Experts give conflicting advice to the government; the bickering couple cannot know whether their past signals their future.)

- **Fuzzy evaluation.** *The criteria for evaluating the future are ambiguous and multidimensional*. (The couple must consider their feelings, children, finances; careers bring different forms of satisfaction.)

- **Commitment.** *Decisions and outcomes are often separated in time, so we must manage our course of action as the situation evolves.* (People must sustain career training and organizations their plans for years on end.)

- **Sense-making.** *The right decision about the future depends on grasping the present.* (The government considers which epidemiological models are most plausible; the widow makes her best guess about what caused the noise.)

- **Imagination.** *Since the future does not yet exist, we must imagine it to evaluate its desirability*. (Decisions about love, appliances, intruders, and viruses require future forecasts.)

- **Social embeddedness.** *The decision depends both on our beliefs and values, and those of others.* (The government persuades the public to implement its policies; beliefs about marriage are shaped by our culture and media diet.)

These challenges are ubiquitous, yet their solutions elude dominant theories of decision-making.

This paper presents *Conviction Narrative Theory* (CNT)—an account of choice under radical uncertainty. According to CNT, *narratives*—mental representations that summarize relevant causal, temporal, analogical, and valence information—are the psychological substrate underlying such decisions. Narratives support and link four processes—*explanation* (structuring evidence to understand the past and present, yielding emotional satisfaction), *simulation* (generating *imagined futures* by running the narrative forward), *affective evaluation* (appraising the desirability of imagined futures and managing commitment toward a course of action over time), and *communication* (transmitting decision-relevant knowledge across social networks to justify, persuade, and coordinate action). Narratives are why the above-mentioned properties so often co-occur: In contexts marked by radical uncertainty and fuzzy evaluation, we use narratives to make sense of the past, imagine the future, commit to action, and share these judgments and choices with others.

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Narratives bubble beneath every example above. Governments debate whether a virus is more like flu or plague; these narratives yield very different explanations of the situation, hence predictions about the future, hence emotional reactions to particular options. The couple can interpret their fights as signaling differences in fundamental values or resulting from temporary stresses; either narrative can explain the fights, portending either a dark or rosy future. The toaster CEO might consider her company ossified, complacent, or innovative; these narratives have different implications about the risks and benefits of new ventures, motivating different decisions. In each case, the decision-maker's first task is to understand the current situation, which informs how they imagine a particular choice would go, which is deemed desirable or undesirable based on how the decision-maker would feel in that imagined future.

Narratives pervade decision-making. This article explains why and how.

2. The Logic of Decision

2.1. Two Problems

Any theory of decision-making must account for how beliefs and values yield action. We divide this question into two problems—*mediation* and *combination*.

2.1.1. The Mediation Problem

Since data must be interpreted to be useful, decision-making requires a mental representation—a *currency of thought*—mediating between the external world and our actions (dashed lines in Figure 1). When we face a decision, we form beliefs—based on prior knowledge and new data—to characterize what will likely happen given potential actions. Those beliefs must be represented in a format that can be combined with our values to guide action (Baumeister & Masicampo, 2010). Put differently, external *data* or raw facts do not become actionable *information* until interpreted in conjunction with our broader knowledge (Tuckett et al., 2020). The burglar must consider, were he to burgle, the likely outcomes (beliefs) and their desirability (values). Some mental representation must simultaneously be the *output* of the reasoning process that judges what will happen and an *input* to the decision-making process that combines those beliefs with each outcome's desirability.

In classical decision theory, the currency of thought is *probability*—continuous values that quantify risk. The burglar's decision depends on his perceived chance he will be caught (*C*) or not caught (*NC*). But this assessment depends potentially on many things—the police presence, burglar's skill, odds the inhabitants are home, etc. This data must be aggregated through Bayesian inference (Section 4.1), combining prior knowledge with new evidence.

The burglar weighs the evidence, assigning 0.2 probability to *C* and 0.8 to *NC*. These probabilities summarize all relevant data about the *external* world in a format used *internally* to combine these beliefs about outcomes with values about their desirability. Probabilities solve the mediation problem because a single representation can be the output of belief-formation and the input to decision-making.

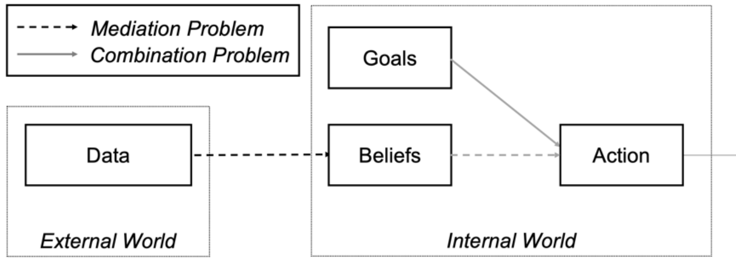

Figure 1. The logic of decision. Decisions reflect both data picked up from the external world—including the social environment—and internally derived goals. The mediation problem (dashed lines) reflects the need for an internal representation—a currency of thought—that can mediate between data from the external world and actions decided internally. The combination problem (gray lines) reflects the need for a process—a driver of action—that can combine beliefs and goals to yield actions. In classical decision theory, the currency of thought is probability and the driver of action is expected utility maximization. In CNT, the currency of thought is narratives, and the driver of action is affective evaluation.

2.1.2. The Combination Problem

Decision-making requires a process—a *driver of action*—that combines beliefs and values to yield action. The burglar must not only assess the likelihood of being caught or not, but how bad or good that would be. If the mediation problem has been solved, we have a suitable representation of likelihood to combine with value judgments. Yet, a further principle must govern this combination.

In classical decision theory, the driver of action is *utility-maximization*: Disparate sources of value are aggregated into an outcome's *utility*, multiplied by each outcome's probability to yield an option's *expected utility*. The decision rule is simply to maximize this quantity. The burglar would consider the sources of (dis)utility associated with being caught (*C*)—social stigma, financial costs, prison—and with not being caught (*NC*)—newfound wealth, perhaps guilt. The utility of *C* and *NC* might be –8 and +3, respectively. Then, the expected utility is each state's utility, weighted by its probability:

$$\mathrm{U}(C)^*\mathrm{P}(C) + \mathrm{U}(NC)^*\mathrm{P}(NC) = (0.2)(-8) + (0.8)(3) = +0.8$$

Crime is expected to pay, so the rational burglar would attempt the burglary. Although expected utility maximization is not the only justifiable decision rule, philosophers and economists have marshalled powerful arguments for its rationality (Savage, 1954; von Neumann & Morgenstern, 1944).

2.2. Two Puzzles

The reader may already feel uneasy about these admittedly-ingenious solutions to the mediation and combination problems: *Where do these numbers come from?* Varieties of this puzzle afflict both probabilities and utilities.

2.2.1. Radical Uncertainty

Radical uncertainty characterizes situations when probabilities are unknowable (Kay & King, 2020; Knight, 1921; Volz & Gigerenzer, 2012), because we do not know the data-generating model or cannot list all possible outcomes. Debates over pandemic policy are riddled with uncertainty about the infection itself (contagiousness, lethality) and policy responses (efficacy, unintended consequences). We don't know the right model for any of these—without a model, how do we calculate probabilities? Moreover, we cannot enumerate the potential implications of each policy choice—without a list of outcomes, how do we assign probabilities to them? Similar problems afflict our other examples earlier—try assigning probabilities to the prospects of the bickering couple, the toaster CEO, or, indeed, the burglar, and it becomes clear that radical uncertainty haunts many everyday decisions.

Radical uncertainty has many sources. Some derive from *aleatory uncertainty* from the world itself (Kay & King, 2020):

- **Non-stationary distributions.** Stationary processes have constant probability distributions over time, learnable over repeated observations. Many real-world processes are *non-stationary*. Each time a pathogen mutates, its previously observed properties—the severity of disease in population sub-groups, its responsiveness to treatments and prevention by vaccines—change in unknowable ways. The question "What is the risk of dying of a mutating virus if I contract it in 6 months?" has no answer.

- **Agency.** Human behavior is often unpredictable. This is especially obvious for pivotal historical events—the assassination of Caesar, Putin's invasion of Ukraine—but smaller forms of agency-driven uncertainty render foggy whole swaths of the future. Technological innovation depends on the insights and happenstance of individuals (Beckert, 2016; Knight, 1921; Ridley, 2020), yet produce profound discontinuities. Behavior emerging from interactions among collectives adds further uncertainty, as illustrated by waves of virality in social media. The sweeping effects of government policies often depend on the preferences of one person or unpredictable interactions among a group. The COVID-19 pandemic would have had a far different shape were it not for many unpredictable choices—the rapid development of vaccines by scientists, the often-haphazard decisions of politicians.

Radical uncertainty also results from the *epistemic* limitations of our finite minds:

- **Information limits.** Often, we lack information to fully understand a situation. In the early days of a pandemic, we know little about how a pathogen is transmitted or who is afflicted. At other times, we have *more* information than we can process: An endless parade of potentially relevant data resides in our environment and the deepest trenches of memory. There is often an abundance of relevant information, if only we knew where to find it. But life is not an exam problem—information is not branded with "relevant" or "irrelevant."

- **Specification limits.** When we do not know the data-generating model, we often cannot rationally assign precise probabilities (Goodman, 1955). This means that Bayesian inference—combining precisely expressed prior beliefs with quantitative assessments of how well the data fits each hypothesis—is often mathematically ill-posed. Much thought is instead more qualitative (Fisher & Keil, 2018; Forbus, 1984); while this can create bias, it is often unclear even normatively how to assign precise values. To generate probabilities, data must be interpreted; interpretation requires a model; and our models, for all but the simplest situations, are incomplete.

- **Generation limits.** Most realistic problems are open-ended, requiring us to generate our own hypotheses. There are endless reasons why a new cluster of virus cases can arise—a resident returned from abroad, a tourist brought the virus, a superspreader event happened, a new variant has arisen. Even if we can *test* individual explanations, we will never be able to *list* all possible explanations. Our imaginations are limited and so we cling to small numbers of especially plausible hypotheses—raising the question of where they come from.

- **Capacity limits.** Our minds have limited attention, working memory, and inference capacity (Miller, 1956; Murphy & Ross, 1994). Bayesian calculations rapidly reach absurd calculational complexity. For each calculation of a posterior, we must separately calculate the prior and likelihood and combine them, and an inference may require posteriors for many plausible hypotheses. This is bad enough, but often our inferences are chained (Steiger & Gettys, 1972). In the case of a pandemic, we cannot generate reliable predictions of how death numbers will respond to policy interventions because the responses both of individuals (e.g., distancing behavior) and the virus (e.g., mutations) are uncertain and intertwined in feedback loops.

Probabilities, by definition, are inappropriate under radical uncertainty. Although uncertainty has long been a thorn in the side of economics (Camerer & Weber, 1992; Knight, 1921; Ellsberg, 1961), almost all economic models assume that outcomes can be enumerated and assigned probabilities. Even behavioral models typically replace optimal with biased probabilistic processing (Tversky & Kahneman, 1979). This can work when the underlying model really is known, as in gambling. But real-world decision-making often resembles poker more than roulette—probabilities only get you so far.

2.2.2. Fuzzy Evaluation

Fuzzy evaluation characterizes situations in which utilities cannot be evaluated. Reasons include:

- **Incommensurable attributes.** We rarely evaluate choice objects along a single dimension, but must somehow combine multiple dimensions into an overall summary judgment. Writing an academic article mingles the joy of intellectual work and the pride of completion with the frustration of slow progress and the angst of possible rejection. Filing for divorce merges the pain of leaving behind shared history with the prospect of turning over a new leaf. These potential options are difficult to evaluate because these attributes are along almost totally unrelated dimensions that resist placement onto a common scale (Walasek & Brown, 2021).

- **Incomparable outcomes.** When we compare objects along a single dimension, we can often simply rank them pairwise along that dimension. But so often, one object excels on one dimension while another object excels on another. When the attributes are incommensurable, trading off attributes across choice objects is necessary to make a choice, yet it is often unclear how to do so rationally (Walasek & Brown, 2021). For example, consider choosing between careers as a clarinetist or lawyer (Raz, 1986). Neither career is clearly better, nor are they equally good—they are good in *different* ways: One involves more self-expression, the other more opportunity to improve the world. The relative desirability of these attributes eludes quantification. Imagine increasing the clarinetist's salary by 1%. Although clearly better than the original clarinetist job, it is still not clearly better than the lawyer job, violating transitivity (Sinnott-Armstrong, 1985). Gaining further information is unlikely to help here, where there are good arguments for and against each choice—a recipe for ambivalence (Smelser, 1998).

- **Non-stationary values.** Our values may be unstable over time, yet we often make decisions for our future selves. Innovators face the challenge that consumers may not know what they like until they actually experience it—as in Henry Ford's (apocryphal) remark that if he had asked customers what they wanted, they would have said "faster horses." We decide whether to have a first child before the experience of parenthood radically alters our priorities (Paul, 2014). Just as beliefs are uncertain when probability distributions are non-stationary, so are values uncertain when they change unpredictably. Moreover, even if one could accurately predict one's future values, how can *current* decisions be governed by *future* preferences?

Just as neoclassical and behavioral models differ in their approach to uncertainty mainly in assuming optimal versus biased probabilistic processing, their approach to preferences differs mainly in adding additional sources of utility (e.g., social utility; Fehr & Schmidt, 1999) or biases (e.g., reference-dependent preferences;

Tversky & Kahneman, 1979). Such approaches are poorly suited to many everyday decisions where utilities are non-calculable and fuzzy evaluation reigns.

3. Conviction Narrative Theory

Conviction Narrative Theory (CNT) characterizes the social and informational context in which decision-making occurs and the cognitive and affective processes governing it. CNT provides alternative solutions to the mediation and combination problems that eschew probabilities and utilities.

Under radical uncertainty and fuzzy evaluation, decision-making requires us to extract relevant information by explaining the past, use that information to predict the future, and evaluate possible futures. CNT posits *narratives* as the key mental representation underpinning these processes: A narrative is selected that best explains the data, which is then used to imagine possible futures given potential choices, with emotional reactions to those imagined futures motivating choices—producing conviction to take sustained action (Tables 1 and 2). (For precursors, see Chong & Tuckett, 2015; Tuckett, in press; Tuckett et al., 2020; Tuckett & Nikolic, 2017.)

Context. Although not every decision is taken under radical uncertainty and fuzzy evaluation—probabilities and utilities are well-suited for studying gambles typical in risky-choice experiments—these properties are common in everyday decisions that do not wear numbers on their sleeves. Despite drawing on fewer resources by avoiding probabilities and utilities, CNT draws on more resources in another sense—decisions are typically socially embedded, with beliefs and values influenced by others and subject to cultural evolution (Section 9). This often permits reasonable decision-making in the absence of probabilities and utilities.

Representations. CNT posits *narratives* as structured, higher-order mental representations summarizing causal, temporal, analogical, and valence structure in a decision domain (Section 5). For example, the widow hearing the noise has different causal theories of why sounds occur at different times; draws analogies between the present case and similar situations; and keeps track of the nefarious or innocent intentions implied. This knowledge might be represented in 'burglary' versus 'noisy cat' narratives. Similarly, different individuals may hold sharply distinct narratives about a global pandemic by drawing on different causal and analogical theories (see Figure 5 in Section 5).

Context	***Radical Uncertainty***	Many everyday decisions require beliefs about outcomes that are not finitely enumerable nor their probabilities calculable.
	Fuzzy Evaluation	Many everyday decisions require trade-offs of values that are incommensurable across choice objects and unstable over time.
	Social Embeddedness	Beliefs and values are influenced by social context.
Representations	***Narratives***	Structured, higher-order mental representations incorporating causal, temporal, analogical, and valence information about agents and events, which serve to explain data, imagine and evaluate possible futures, and motivate action.
	Imagined Futures	Iconic representations of specific sequences of imagined events generated from a narrative in response to a particular choice being contemplated.
	Narrative Fragments	Subsets of the elements in a narrative which can be readily communicated.
	Shared Narratives	Elements of narratives held in common across members of a social

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		group, transmitted through narrative fragments.
Processes	***Explanation***	The process of selecting and constructing narratives based on evidence available from the informational, social, and internal cognitive environment, using heuristics and affect.
	Simulation	The process of generating imagined futures by projecting a narrative forward.
	Affective Evaluation	The process of evaluating imagined futures by reacting emotionally to them.
	Communication	The processes by which narratives are socially shared, propagating through social networks.

Table 1. Elements of Conviction Narrative Theory. Description of key aspects of the decision-making context, mental representations, and mental processes invoked by CNT.

Despite the ecumenical representational format, narratives are constrained by their functions: They explain and summarize data, facilitate predictions, and motivate and support action. These correspond to the three key processes underlying individual decision-making in CNT, which are intertwined with narratives (Figure 2).

Processes. *Explanation* makes sense of available data in a unified mental framework by evaluating potential narratives (Section 6). For example, the widow would consider the evidence—time of day, type and duration of noise—to adjudicate the burglar versus noisy cat narratives. Explanation draws on multiple sources of evidence, including prior beliefs, shared narratives, and new observations. Because probabilities are not available under radical uncertainty, heuristics—simple rules relying on small numbers of cues—are used to evaluate narratives, including those exploiting causal, analogical, and temporal structure embedded in narratives. These heuristics are often implemented through affect—which narrative *feels* right.

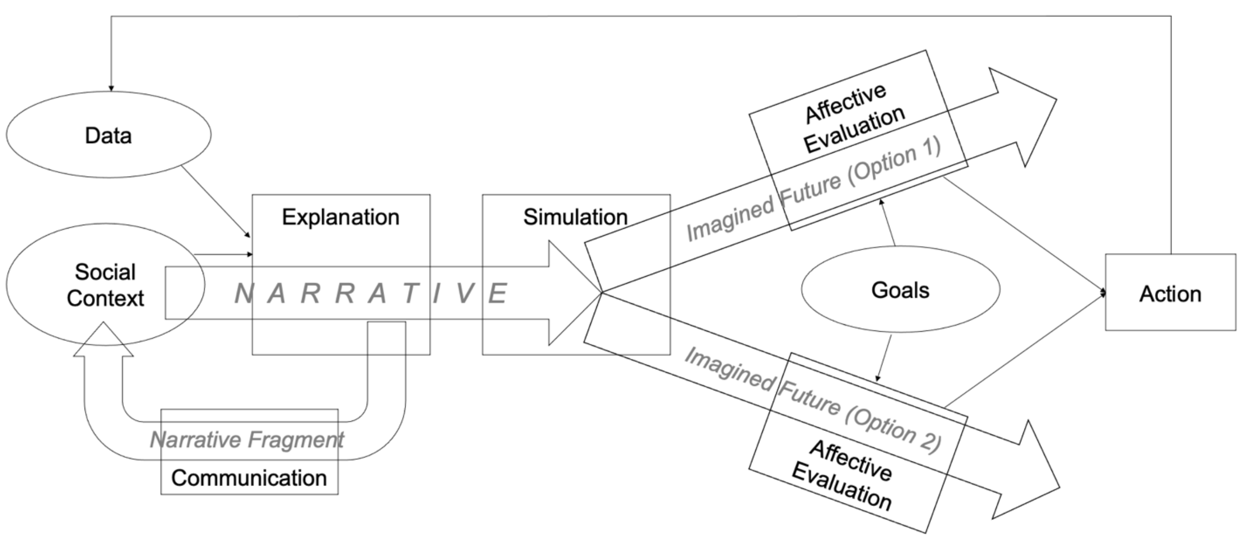

Figure 2. Representations and processes in Conviction Narrative Theory. Narratives, supplied in part by the social environment, are used to explain data. They can be run forward in time to simulate imagined futures, which are then evaluated affectively considering the decision-maker's goals. These appraisals of narratives then govern our choice to approach or avoid those imagined futures. The figure also depicts two feedback loops: Fragments of narratives that are successfully used may be communicated recursively back to the social context, evolving narratives socially, and our

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actions generate new data that can lead us to update narratives, evolving narratives individually. (*Block arrows depict representations; rectangles depict processes; circles depict sources of beliefs and values, which are inputs to processes via thin arrows*.)

The narrative is then used to *simulate* the future (Section 7). Given the burglary narrative, the widow would consider the likely outcome if she were to investigate (being violently attacked), ignore the noise (losing possessions), or equip her investigation with a baseball bat (showing the burglar who's boss). Whereas explanation works by thinking *across* narratives and adopting the most plausible, simulation works by thinking *within* the adopted narrative and imagining the future. We project ourselves into a narrative and imagine what would happen if an action is taken by "running" causation forward. This process generates a representation we term an *imagined future*—a specific sequence of imagined events, represented iconically with a temporal dimension; unlike a narrative, it need not include detailed relational information except an ordered sequence of events. However, imagination has sharp limits—rather than imagining multiple potential futures and 'averaging' them, we typically imagine only one future for each choice.

We then *affectively evaluate* that imagined future and take (sustained) action (Section 8). Emotional responses to that future combine beliefs and values. When emotions such as excitement or anxiety are triggered by contemplating an imagined future, we are motivated to approach or avoid that future (Elliot, 2006). The widow imagines an unpleasant future from ignoring the noise, and a more palatable one from a cautious investigation, motivating approach toward the latter future. CNT describes two ways emotions can appraise futures: A *default strategy* based on typical appraisal dimensions used by our affective systems, and an *ad hoc strategy* based on the active goal(s) in our goal hierarchy (Section 8.2).

Emotions are also needed for *maintaining* decisions (Section 8.3). Uncertainty breeds ambivalence, with good arguments for multiple options and the need to sustain decisions over time. When emotions become embedded in narratives, such conviction narratives can manage the incorporation of new information into decision-making while maintaining commitment. As the widow approaches the noise's source, it is natural to feel deeply ambivalent about her choice. Confidence in a stable narrative and imagined future helps to maintain a consistent course of action. When used adaptively, decision-makers incorporate new information from the world into their narratives, creating feedback loops and allowing us to improve repeated or sustained decisions over time.

Beyond these backbone operations of choice—explanation, simulation, evaluation—narratives underlie a fourth function: *Communication* (Section 9). Whereas narratives in our definition are mental representations embedded in individual minds, some elements are shared in common across a social group; we refer to this set of common elements as a *shared narrative*. Since these elements are shared only piecemeal (primarily through language), it is these *narrative fragments* that are communicated and which shape and maintain shared narratives. Communication is another way that narratives can participate in feedback loops, now at the collective level: Shared narratives propagate, adapt, and die according to the principles of cultural evolution, permitting learning not only at the individual but at the cultural level. Shared narratives facilitate coordination when used to persuade others and maintain reputation. They propagate when they are catchy enough to be shared, memorable enough to store, and relevant enough to guide decisions.

	Proposition
Narratives	Narratives are structured, higher-order representations.
	Narratives characterize real-world decisions under radical uncertainty.
Explanation	We use a suite of explanatory heuristics to evaluate narratives.
	Explanatory fit is experienced affectively.

Simulation	Imagined futures are simulated by projecting a narrative forward. Imagined futures are simulated one at a time.
Affective Evaluation	Affective evaluations of imagined futures motivate choices. Imagined futures can be appraised on default or ad hoc dimensions. Emotions are used to manage decisions extended over time.
Communication	Shared narratives facilitate social coordination. Shared narratives shape social learning and evolve. Shared narratives propagate through social networks.

Table 2. Propositions of Conviction Narrative Theory. These propositions are elaborated in Sections 5–9 with supporting evidence.

Nowhere in this proposed process do probabilities or utilities appear; instead, ecologically and cognitively available substitutes play leading roles. In lieu of probabilities to assess narratives, heuristics are used, with narratives arising from the social environment and subjected to cultural evolution; instead of probabilities assigned to imagined futures, the single likeliest imagined future is adopted and evaluated. Rather than utilities assigned to particular outcomes over many dimensions, emotions are felt in response to imagined futures, dependent on the decision-maker's goals.

4. Relationship to Alternatives

Although we believe our model is the most comprehensive explanation of how and why narratives predominate in decision-making, CNT draws on several related approaches.

4.1. Rational Approaches

Bayesian cognitive science models go beyond classical decision theory in showing how probabilities can be calculated and applied to many tasks (Tenenbaum et al., 2011). First, such models specify the hypothesis space. For example, the CEO considering a new blender model might entertain three hypotheses: "We cannot engineer the blender," "We engineer the blender but cannot successfully market it," "The blender expansion succeeds." The reasoner assigns prior probabilities to the hypotheses, evaluates each hypothesis's fit with the data, and combines these using Bayesian inference. For example, the CEO might assign priors of 0.4, 0.35, and 0.25 to these hypotheses. As evidence accumulates—engineers develop a prototype, marketers run focus groups—she considers the likelihood of this evidence under each hypothesis, using Bayes' theorem to combine likelihoods with priors. Despite the simplicity of this toy example, Bayesian cognitive science models make a range of substantive and interesting claims about how people think in a vast array of contexts.

Many critiques have been written of these models (Bowers & Davis, 2012; Jones & Love, 2011; Marcus & Davis, 2013), and we do not endorse all points of criticism. From our perspective, Bayesian approaches potentially work, both in principle and practice, quite well under risk. But their inescapable limitation is the same as for classical decision theory—probabilities cannot be modeled under radical uncertainty, which can interfere with each modeling step:

- **Hypothesis space.** Many problems resist an enumeration of possible outcomes. The CEO has neglected many other possibilities—competitors entering the blender market, engineers generating a prototype no better than competitors', regulators blocking the expansion. This is due to both aleatory uncertainty (some possibilities cannot be imagined even in principle because the future is unknown—the "unknown unknowns") and to generation limits (our finite cognitive capacity to imagine possibilities in open-ended problems).

- **Priors.** It is often unclear even in principle how to rationally set priors. How did the CEO assign a 0.4 probability to her engineering team's failure? Why not 0.2, 0.35, or 0.7? Is it reasonable to use the base rate of engineering team failures given that this product has never before been designed? This is a specification limit—one cannot non-arbitrarily favor one value over another within a range of plausible values. This not only limits the psychological plausibility of these models, but can be problematic for the models themselves since the specific priors chosen sometimes drive the model's fit (Marcus & Davis, 2013).

- **Likelihoods.** Likelihoods reflect the probability of the evidence conditional on each hypothesis. This raises three problems in realistic contexts. First, information limits: How do we know what evidence is relevant? The CEO may scan the newspaper, consumer research, and marketing reports to grasp the blender market, but will struggle to know which pieces of information bear on her hypotheses. Second, as for priors, specification limits: How do we assign probabilities non-arbitrarily? How is she supposed to estimate the likelihood of particular focus group feedback conditional on the product's future success? Third, capacity limits: With very many pieces of evidence and hypotheses, the amount of calculation rubs up against memory and attention limits.

- **Updating.** Bayesian inference itself quickly approaches capacity limits as the number of hypotheses increases, since priors and likelihoods for each hypothesis must be stored and combined. This is especially problematic for the chains of inference that are common in real-world problems. The probability of successful roll-out depends on the quality of the product, the performance of the marketing team, word-of-mouth, predictions made by analysts and retailers, and countless other factors, often mutually dependent. Moreover, the problems surrounding hypothesis spaces, priors, and likelihoods compound at each step.

Rational approaches—both classical and Bayesian varieties—are nonetheless valuable. They can characterize 'small-world' problems, such as risky decisions with enumerable outcomes and probabilities; sometimes provide normative benchmarks for assessing human decisions; provide valuable insights for designing artificial systems (Lake et al., 2017); and provide insight at Marr's (1982) computational level by characterizing the goals of a cognitive system. And although probabilistic approaches cannot capture cognition under radical uncertainty, they have inspired some of the boundedly rational approaches discussed next.

4.2. Boundedly Rational Approaches

Both classical and Bayesian approaches have been criticized for their lack of psychological realism, leading to several varieties of *bounded rationality* as amendments. Their core insight is that, although our minds are limited and prone to error, we get quite far with these limited resources: We can be rational within the bounds of our finite minds.

The dominant theoretical style in behavioral economics is surprisingly continuous with neoclassical modeling. Traditional models assume that economic agents are rational, then specify the institutional environment through which the agents interact (e.g., firms and consumers in a competitive market with priced goods) and examine the resulting equilibrium. Behavioral models use the same steps, but tweak the agents to incorporate biases or non-standard preferences, as explained in Section 2.

Like classical approaches, we believe these models produce valuable insights, particularly how small changes to the assumed psychology of economic agents qualify the results of standard models. Yet, such models struggle with radical uncertainty and fuzzy evaluation. The same problems that plague classical models with probabilities apply to behavioral models with 'decision weights': Such models may capture real psychological biases in how people process probabilities, yet assume probabilities *exist* to be processed. This makes sense for some formal models and laboratory tasks, but not when probabilities do not exist (Section 2.2.1). Likewise, models that stuff the utility function with goodies can capture genuine trends in preferences, but create an illusion of precision when evaluation is fuzzy and options are incommensurable (Section 2.2.2).

Several important principles of bounded rationality, however, do not depend on the intelligibility of optimization:

- **Resource rationality.** In coining the term 'bounded rationality' Simon (1957) did not view humans as capriciously irrational, but as managing the best we can given our cognitive and environmental limitations. This approach has been refined in sophisticated models of *resource rationality* (Lieder & Griffiths, 2020), emphasizing the rationality of simplifying strategies such as sampling (Sanborn et al., 2010). Rationing limited resources is one reason to adopt simplifications—such as narrative thinking—in the face of the calculational difficulties of uncertainty. Equally importantly, probabilistic strategies under uncertainty are not always capable of giving any answer at all.

- **Heuristics.** A heuristic is a fallible-but-useful shortcut. Heuristics are often discussed in contexts where correct answers exist but algorithmic approaches are infeasible or knowledge too limited to provide an optimal answer: Some researchers ("heuristics-and-biases") emphasize the 'fallible' part of 'fallible-but-useful', and others ("fast-and-frugal") the 'but-useful' part (Gigerenzer, 2008; Tversky & Kahneman, 1974). For our purposes, we note that heuristics also may be useful in situations where no objectively correct answer exists, yet some answers are more reasonable than others.

  A parallel debate has raged in normative and descriptive ethics. Utilitarianism emphasizes calculation (Bentham, 1907/1789), positing a duty to maximize social utility. Yet just as Bayesian calculations are often impossible in principle, utilitarian calculations often fail in real-world situations. Aristotle (1999/350 BCE) bemoans the impossibility of a complete theory of ethics, instead urging us to cultivate habit and virtue to do the right thing in particular situations. Indeed, people distinguish between 'rational' and 'reasonable' behaviors (Grossmann et al., 2020), with the former characterized by optimization and abstract universalism, the latter by pragmatism and context-sensitivity (Rawls, 2001; Sibley, 1953). This is likely why descriptive accounts of moral decision-making point to tools such as rules (Greene et al., 2001; Kant, 2002/1796; Mikhail, 2007), norms (Nichols, 2002), sacred or protected values (Baron & Spranca, 1997; Tetlock, 2003), and character virtues (Johnson & Ahn, 2021; Uhlmann et al., 2015), which often act like heuristics (De Freitas & Johnson, 2018; Sunstein, 2005). For moral decisions, like many everyday choices, often no clearly correct option exists, yet some are more readily justifiable.

- **Ecological rationality.** A crucial point made by some researchers from boundedly rational traditions is that decision-making is adapted to real environments, so seemingly irrational behaviors observed in atypical contexts may be manifestations of more deeply rational—or at least adaptive—behaviors (Todd & Gigerenzer, 2007). If most everyday decisions are taken under radical uncertainty, then behaviors that may be adaptive in the real world may manifest as demonstrably suboptimal decisions in the context of risky (often lab-based) contexts.

Narrative approaches to decision-making are compatible with these insights, and can be considered a species of bounded rationality—albeit, at least for CNT, one for which the appropriate benchmark is *reasonableness* rather than *rationality*.

4.3. Narrative Approaches

Several researchers in both psychology and economics have argued that narratives guide decision-making.

From early days in the heuristics-and-biases tradition, causal thinking was thought to play a privileged role in judgment (Kahneman & Tversky, 1982), such as our ability to use base rates (Ajzen, 1977; Krynski & Tenenbaum, 2007; Tversky & Kahneman, 1980; cf. Barbey & Sloman, 2007; Gigerenzer & Hoffrage, 1995; Koehler, 1996). However, the first decision-making model to consider detailed cognitive mechanisms underlying narrative thought was the Story Model of Pennington and Hastie (1986, 1988, 1992, 1993), most famously applied to juror decisions. In their model, jurors reach verdicts by constructing causal stories and assigning the story to the most appropriate verdict category (e.g., manslaughter, not-guilty). In their studies, participants generated verdicts based on realistic trial evidence. When describing their reasoning, participants overwhelmingly supported their verdicts with causal stories (describing intentions and behaviors) rather than unelaborated lists of facts, with these stories differing greatly across individuals depending on their verdict (Pennington & Hastie, 1986). Manipulating the ease of constructing coherent stories (scrambling evidence order) dramatically shift participants' verdicts (Pennington & Hastie, 1988, 1992). Although the Story Model's legal applications are best-known, it has also been applied to other contexts including economic decisions (Hastie & Pennington, 2000; Mulligan & Hastie, 2005).

Research since this seminal work has developed in two directions. In cognitive science, increasingly sophisticated theories model how people think about networks of causal relationships (Gopnik et al., 2004). For example, Sloman and Hagmayer (2006) argue that people conceptualize their decisions as interventions on a causal network—an idea in sympathy with CNT, wherein choice points in a narrative are opportunities to select among different imagined futures implied by the narrative. A separate but kindred line of work on the Theory of Narrative Thought (Beach, 2010; Beach et al., 2016) emphasizes the pervasive role of narratives in memory and cognition, and, like CNT, highlights the importance of narratives for forecasting (Beach, 2020).

A second direction (Abolafia, 2020; Akerlof & Shiller, 2009; Akerlof & Snower, 2016; Shiller, 2019) emphasizes the role of shared narratives in economic outcomes. Shiller argues that when shared narratives go viral, they influence expectations about the future, shaping macroeconomic activity. Shiller's view also provides a powerful role for contagious emotions, especially excitement and panic.

CNT develops these ideas in a third direction: Incorporating ideas about narrative decision-making into a broader framework that elaborates processes and mechanisms, explains how narratives and emotion combine to drive and support action, and accounts for the role of cultural evolution of narratives to render decision-making adaptive even under radical uncertainty. We see CNT as complementing rather than contradicting these perspectives, developing these approaches to the next stage in their evolution.

5. Narratives

Prior work has not coalesced around a single definition of 'narrative', much less a single notion of representation. For example, Beach (2010) defines 'narrative' as "…a rich mixture of memories, of visual, auditory, and other cognitive images, all laced together by emotions to form a mixture that far surpasses mere words and visual images in their ability to capture context and meaning," while Shiller (2019) follows the Oxford English Dictionary in defining it as "…a story or representation used to give an explanatory or justificatory account of a society, period, etc." (quoted in Shiller, pg. xi). Meanwhile, Pennington and Hastie (1992) say that stories "…could be described as a causal chain of events in which events are connected by causal relationships of necessity and sufficiency…." The hierarchical structure of stories—for instance, that events can be grouped into higher-order episodes—is also often noted as a common feature (Abbott et al., 1985; Pennington & Hastie, 1992). Across these conceptions, causation is central but not the only hallmark of narratives—they provide meaning by explaining events (Graesser et al., 1994; Mandler & Johnson, 1977; Rumelhart, 1975).

In our view, ordinary causal models (Pearl, 2000; Sloman, 2005; Spirtes et al., 1993) are a crucial starting point, yet not quite up to the task of representing narratives. (That said, some progress has been made toward formalizing some economic narratives in this way; Eliaz & Spiegler, 2018.) For our purposes, causal models have two shortcomings: They do not represent some information—such as analogies and valence—that will prove crucial to narrative thinking; and operations over causal models are usually assumed to be probabilistic—a non-starter under radical uncertainty.

We define narratives as *structured, higher-order mental representations incorporating causal, temporal, analogical, and valence information about agents and events, which serve to explain data, imagine and evaluate possible futures, and motivate and support action over time*. No doubt, this definition itself requires some explanation.

5.1. Narratives are structured, higher-order representations

In a *structured* mental representation, relations are represented among the objects it represents. For example, a feature list is an unstructured representation of a category, whereas a spatial map with every location represented in a precise orientation compared to every other location is highly structured. Similarly, causal models are highly structured, as are representations of categories whose features are related to one another through analogy (Gentner, 1983).

Narratives may have been difficult to pin down in past work because they are structured, like causal models, but contain richer information that is not typically represented in causal models. Specifically, we argue that narratives can represent causal, temporal, analogical, and valence structure. Complicating things further, not all types of structure are necessarily invoked in a given narrative. Narratives are *higher-order representations* that flexibly include lower-order representations.

5.1.1. Causal structure. Narratives represent at least two types of causal relationships: *event-causation* and *agent-causation*. Event-causation can further be sub-divided based on the kind of event (individuals or categories) and how the events are connected (e.g., colliders, chains, or webs).

Event-causation refers to dependency relationships between either individual events (*the Central Bank lowered interest rates, causing investment to increase*) or event categories (*lower interest rates cause increased investment*). Both kinds of event-causal relations are important since narratives incorporate information both about individual events (e.g., the course of my marriage) and event categories (e.g., how relationships work generally), including analogical links between these knowledge types. We are agnostic about the representational format of event-causation, and indeed these representations may involve aspects of networks, icons, and schemas (Johnson & Ahn, 2017). For familiarity, the diagrams we use to depict narratives are elaborated from causal network conventions (Figures 3-6).

Patterns of event-causation also vary in their topology and inference patterns (Johnson, 2019). Three common types of causal patterns in narrative contexts are colliders, chains, and webs (Figures 3a-c).

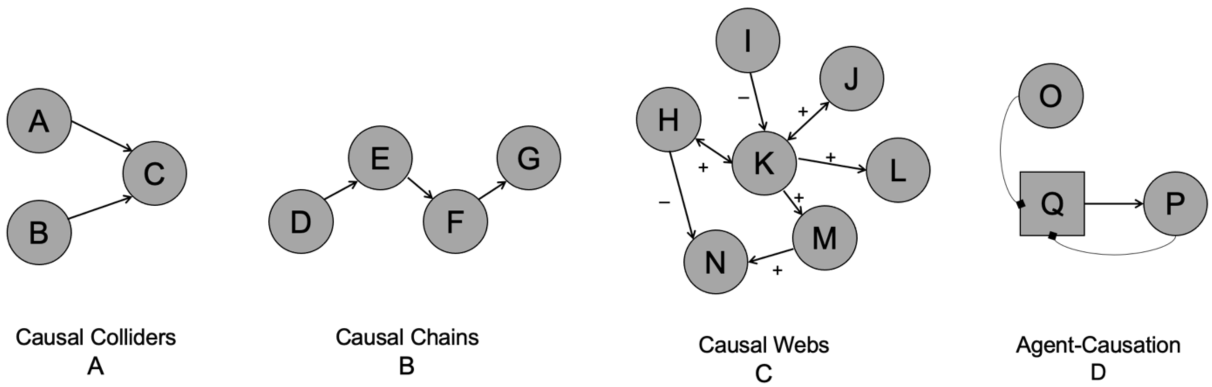

Figure 3. Common causal structures in narratives. In Panel A (a *causal collider*), multiple potential causes (A or B) could explain an event (C); a typical inference problem would be to evaluate A and B as potential explanations of observation C, which may in turn license other inferences about effects of A or B (not depicted here). In Panel B (a *causal chain*), a sequence of causally related events (D, E, F, G) is posited; typical inference problems would be to evaluate whether the overall sequence of events is plausible, or whether an intermediate event (E) is plausible given that the other events (D, F, G) were observed. In Panel C (a causal web), many event types (H–N) are thought to be related to one another, with some relationships positive and others negative, and some bidirectional; typical inference problems would be to evaluate the plausibility of individual links or to infer the value of one variable from the others. In Panel D (*agent-causation*), an agent (Q) considers taking an action (P), based partly on reasons (O) and their judgment of the action itself (P); typical inference problems would be to predict the agent's action based on the available reasons, or infer the agent's reasons based on their actions. (*Circles and squares depict events and agents, respectively; straight arrows depict causal relationships, which could be unidirectional or bidirectional, positive [default or with a '+' sign] or negative [with a '–' sign]; curved, diamond-tipped arrows depict reasons. For causation among events and agents, but not event-types [Panels A, B, and D], left–right orientation depicts temporal order.)*

In a *causal collider* (Figure 3a), we can observe evidence and seek an explanation for it, which may in turn generate further predictions. For example, if a central banker makes some statement, this licenses inferences about the banker's intention, which may yield predictions about the bank's future policies.

In a *causal chain* (Figure 3b), a sequence of events is causally and temporally ordered. Mrs. O'Leary went to milk her cow; the cow objected and kicked a lantern; the lantern started a fire; and so began the Great Chicago Fire (supposedly). A mysterious individual invents blockchain technology; it fills an important economic niche; it gains value; it becomes widely adopted. We can think about the plausibility of these sequences overall, fill in missing events from the chains, and predict what will happen next.

In a *causal web* (Figure 3c), we ask how a set of variables relate to one another—an intuitive theory (Shtulman, 2017). Some intuitive theories probably have innate components (Carey, 2009a), but many decision-relevant intuitive theories are learned. For example, investors must have mental models of how macroeconomic variables such as exchange rates, inflation, unemployment, economic growth, and interest rates are linked (Leiser & Shemesh, 2018), and voters have intuitions about trade, money, and profits (Baron & Kemp, 2004; Bhattacharjee et al., Johnson, Zhang, & Keil, 2018, 2019). These intuitions likely drive much political and economic behavior, yet differ strikingly from economists' consensus (Caplan, 2007; Leiser & Shemesh, 2018). This may reflect both divergences between the modern world and evolved intuitions (Boyer & Petersen, 2018), and the difficulty of correctly extracting causal structure from causal systems with more than a few variables (Steyvers et al., 2003).

Narratives often center around the intentional actions of human agents, and such *agent-causation* appears to be a very different way of thinking about causation. Rather than representing *events* as causing one another (e.g., Alan Greenspan's forming the intention to decrease interest rates caused interest rates to decrease), people sometimes appear to think of *agents* as causing events directly (e.g., Alan Greenspan caused interest rates to decrease). This reflects the intuitive notion that agents have free will; that our choices, when construed as agent-causes rather than event-causes, are themselves uncaused (Hagmayer & Sloman, 2009; Nichols & Knobe, 2007). Agents can act for *reasons* (Malle, 1999); they make intentional choices based on their beliefs and desires which are assumed to be rational (Gergely & Csibra, 2003; Jara-Ettinger et al., 2016; Johnson & Rips, 2015). Complicating things further, reasons are often anticipations of the likely effects of one's action.

5.1.2. Temporal structure. Narratives often, but not always, include temporal information about the order, duration, and hierarchical structure of events. For example, causal chains are necessarily ordered sequences of events because causes occur before effects. At the opposite extreme, temporal order often is lacking entirely from causal webs that depict causality among event *categories* rather than individual events. That said, people can track the order, delay, and part–whole structure of causally related events and use these different types of temporal information to disambiguate causal structures (Lagnado & Sloman, 2006; Rottman & Keil, 2012). For example, sequences of events often are segmented into higher-order episodes, each containing lower-level sub-events (Zacks & Tversky, 2001). This part–whole organization affects causal representations, with higher-level events believed to be both causes and effects of other higher-level events, and low-level events from one high-level cluster believed to affect only low-level events from that same cluster (Johnson & Keil, 2014).

5.1.3. Analogical structure. Both the power and peril of narrative thinking compound when people perform inference not only by causal thinking within a single domain, but across different domains through analogies. Structure-mapping theory (Gentner, 1983) is a model of how people select analogies and use them to make inferences, emphasizing that matches in the *relationships* within a domain make it a good or bad analogy for another domain. Thus, analogy is especially powerful when combined with other relational systems such as causal systems (Holyoak et al., 2010) (Figure 4a).

Analogies are important to narratives for at least two reasons. First, they allow us to use familiar domains to make sense—if imperfectly—of less familiar domains. For example, people have highly impoverished mental models of central banking, but more detailed mental models of cars. In a car, stepping on the gas pedal causes more gasoline to enter the engine, increasing the car's speed. People often use this analogy for discussing and understanding central banking; the central bank prints more money, causing more money to enter the economy, causing the economy to go faster. Second, abstract and gist-like representations apply to a broader set of future situations, particularly when making decisions about the distant future (Schacter & Addis, 2007; Trope & Liberman, 2003). Thus, forming analogical links among specific past events and, ultimately, between specific events and more abstract event categories is crucial for generating generalizable knowledge. This is how our representational system incorporates some aspects of narratives' hierarchical structure.

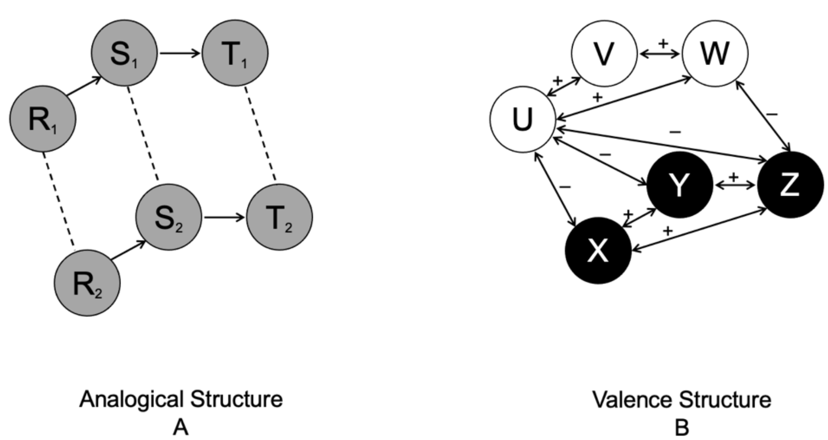

Figure 4. Analogical, valence, and causal structure. In Panel A (*analogical structure*), one causal chain (R_1, S_1, T_1) is analogized to another (R_2, S_2, T_2); typical inference patterns would be to reason from a known sequence (R_1, S_1, T_1) of specific events or schematized depiction of a general causal mechanism to infer the causal–temporal order of a new sequence (R_2, S_2, T_2) or to infer missing events (T_2) given that all other events are observed. In Panel B (*valence structure*),

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positive event types (U, V, W) are seen as bidirectionally and positively related to each other, negative event types (X, Y, Z) are seen as bidirectionally and positively related to each other, whereas negative and positive events are seen as bidirectionally and *negatively* related to each other (Leiser & Aroch, 2009). (*Dashed lines represent analogical correspondences; white and black circles represent 'good' and 'bad' events or event types, respectively.)*

5.1.4. Valence structure. Stories involve good guys and bad guys, goals being achieved or objectives thwarted. Information about norms (right or wrong) and valence (good or bad) is processed rapidly and automatically (Moors & De Houwer, 2010) and influences thinking in many domains including causation (Knobe, 2010). For example, people are likelier to identify norm-violations as causes and non-norm-violations as non-causes (Kominsky et al., 2015), reason differently about the potency of good versus bad causes (Sussman & Oppenheimer, 2020), and tend to think that good events cause other good events (LeBoeuf & Norton, 2012). Macroeconomic understanding is dominated by a "good begets good" heuristic (Leiser & Aroch, 2009), wherein "bad" events (inflation, unemployment, stagnation, inequality) are thought to be inter-related and negatively related to "good" events (price stability, full employment, economic growth, equality) (Figure 4b). In reality, the opposite often holds.

5.1.5. Coherence principles. Given their rich representational capacities, *coherence principles* are needed to constrain narratives' vast possibility space (determining *which* narratives to entertain) and draw inferences about missing information (filling in details *within* a narrative). For example, Thagard (1989) develops a theory of how explanations and evidence cohere, Gentner (1983) presents a theory of how analogical correspondences are drawn, and Rottman and Hastie (2014) summarize evidence about how people draw inferences on causal networks. In addition to principles governing each type of lower-level representation individually, we suggest three principles as starting points for how different types of lower-level representations cohere: (i) Causal, temporal, and valence structure are preserved across analogies; (ii) Causes occur before their effects; (iii) Causal relationships between agents and events with the same valence status ('good' or 'bad') are positive, whereas they are negative for links between 'good' and 'bad' events.

5.1.6. What narratives are not. Narratives are a flexible representational format, but they are not *infinitely* flexible. We (tentatively) suggest the following test for whether a representation is a narrative: It must (i) represent causal, temporal, analogical, or valence information, and (ii) for any of these it does *not* represent, it must be possible to incorporate such information.

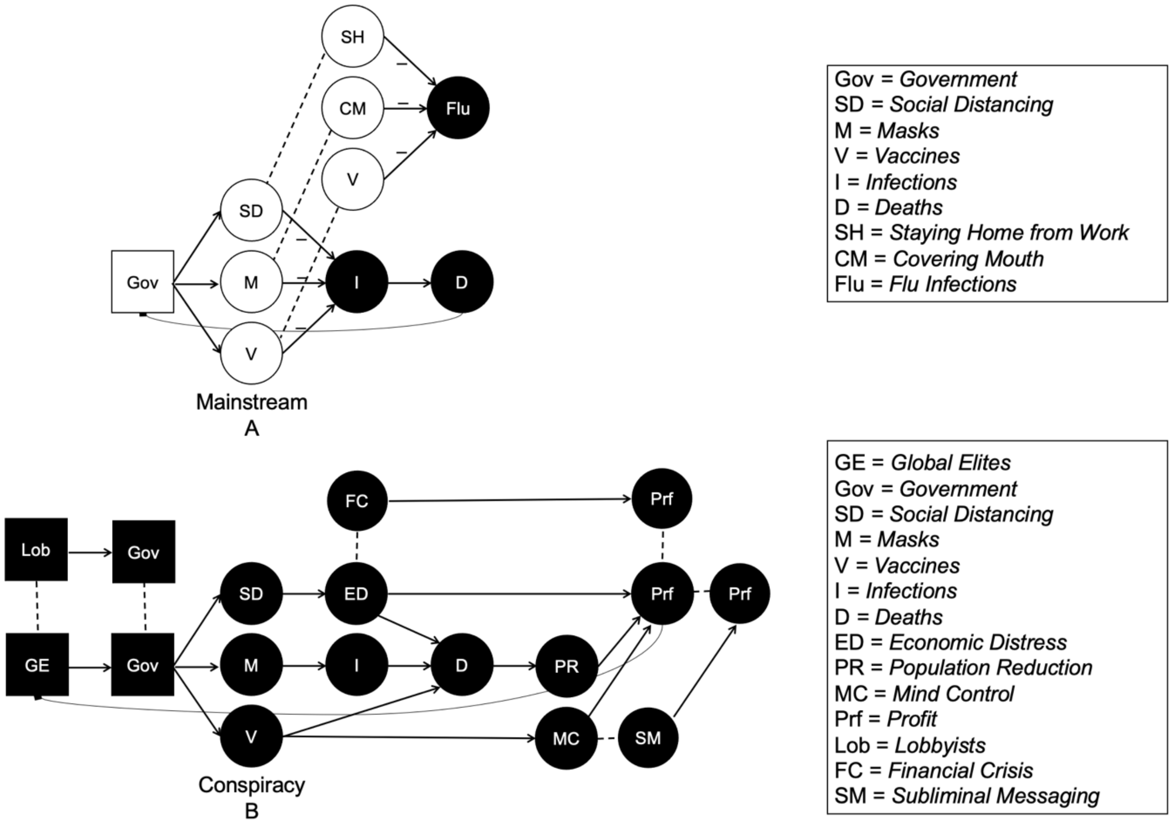

Figure 5. Possible narratives around a global pandemic. Panel A depicts one possible individual's narrative around a global pandemic, which aligns largely with the mainstream view. Infections and deaths (which are bad) are negatively related to interventions such as social distancing, masks, and vaccines, which are themselves results of government action. The government chose these actions for the reason that it would have a preventative effect on deaths. The causal links between each intervention and infection is supported by an analogy to other diseases, such as influenza (i.e., staying home from work, covering one's mouth when coughing, and vaccines all help to prevent flu infections). Panel B depicts one possible conspiratorial narrative around a pandemic. In this narrative, global elites control the government, and are acting so as to increase their profits, which can be done by several channels including economic distress, population reduction, and mind control. These causal links to profitability are supported by their own analogies (e.g., the global financial crisis and subliminal messaging being ways that bankers, corporations, and other elites are thought to increase their profits), as is the idea that the government is captured by unelected elites such as lobbyists for big business. In this narrative, social distancing has little effect on the spread of disease but a strong link to intentional economic distress; masks and vaccines increase infection and death rather than preventing it. For this reason, interventions that are seen as good in the mainstream narrative (because they have a preventive relationship with death) are seen as bad in the conspiracy narrative. These hypothetical narratives will be supported by different social and informational environments, yield conflicting forecasts about the future, and motivate distinctive actions.

This distinguishes narratives from several other kinds of representations, including probabilities, spatial maps, associative networks, images, categories, and logical relations: Such formats do not necessarily include any of the four structured information types. (However, elements of narratives may be linked to such other representations in memory. Indeed, this may be required for narrative simulation to generate iconic representations of imagined futures.)

Figure 5 provides additional examples of possible narratives that might underlie decision-making in the context of a global pandemic, as in one of our running examples.

5.2. Narratives characterize real-world decisions under radical uncertainty

Lab experiments are ill-suited for testing the prevalence of narrative thinking in everyday decision-making. Thus, we bring linguistic and qualitative data to bear.

5.2.1 Linguistic data about macroeconomic narratives. Shiller (2019) uses time-series data from Google N-Grams to track language linked to particular shared narratives. Shiller emphasizes that 'viral' narratives, even if false, can affect macroeconomic events. We would add that shared narratives held true within one's own social network (rather than those held true somewhere else) may be the only way for many to make sense of complex macroeconomic causation.

The shared narrative that labor-saving machinery creates unemployment is perennial. Shiller traces it from Aristotle, through worker riots during the Industrial Revolution, to economic depressions, to present-day concerns about artificial intelligence displacing humans. (Most economists disagree: Since machines increase productivity, wages rise and labor is redeployed to higher-valued uses.) Shiller traces the frequency of 'labor-saving machinery' in books from 1800–2008, with the term peaking during the 1870s depression and again in the lead-up to the Great Depression, with the new term 'technological unemployment' reaching epidemic proportions throughout the 1930s. Plausibly, the fear produced by such narratives exacerbated the underlying problems causing the Depression. Shiller notes that this dovetails with the then-popular theory—never accepted by economists—that machines would produce such plentiful products that we would could never consume it all, generating unemployment. Accordingly, the term 'underconsumption' skyrockets during the Depression. A simplified version of this narrative can be seen in Figure 6a.

Another example concerns boycotts following World War I (Figure 6b). The U.S. dollar experienced 100% inflation after the war, contributing to an anti-business shared narrative, with mentions of 'profiteer' in newspapers peaking at the start of the subsequent depression. According to this narrative, businesses were raising prices to achieve 'excess profits' during the war, explaining the inflation. (Although economists now reject this view of inflation, similar narratives were proposed by some American politicians during the inflation episode in 2022.) Protests ensued, resulting in boycotts on the theory that if consumers did not buy products beyond minimum necessities, the drop in demand would force prices back to 'normalcy'. Although prices never declined to pre-war levels, deflation did indeed result in the 1920–21 depression.

5.2.2 Interview data about microeconomic decision-making. In the same spirit, but using a very different method, Tuckett (2011, 2012; Chong & Tuckett, 2015) interviewed 52 highly-experienced money managers in 2007 and 2011, gathering accounts of decisions to buy or sell securities, using a standardized nonschedule interview approach (Richardson et al., 1965; Tuckett et al., 1985).

These accounts consistently invoked narratives. For example, consider one of the respondents selected at random for detailed presentation in Tuckett (2011, pg. 33). When interviewed, he directed a team of twenty and was personally responsible for allocating stocks into a $35 billion portfolio. His task was to try "to pierce through the smoke and emotion" surrounding market moves and "be contrary to the consensus notion of 'let's wait for the smoke to clear'." "I mean the problem with that philosophy" as he put it, is that "if you wait for everything to be clear you will miss most of the money to be made." "Once everything's clear…it's easy, right?"

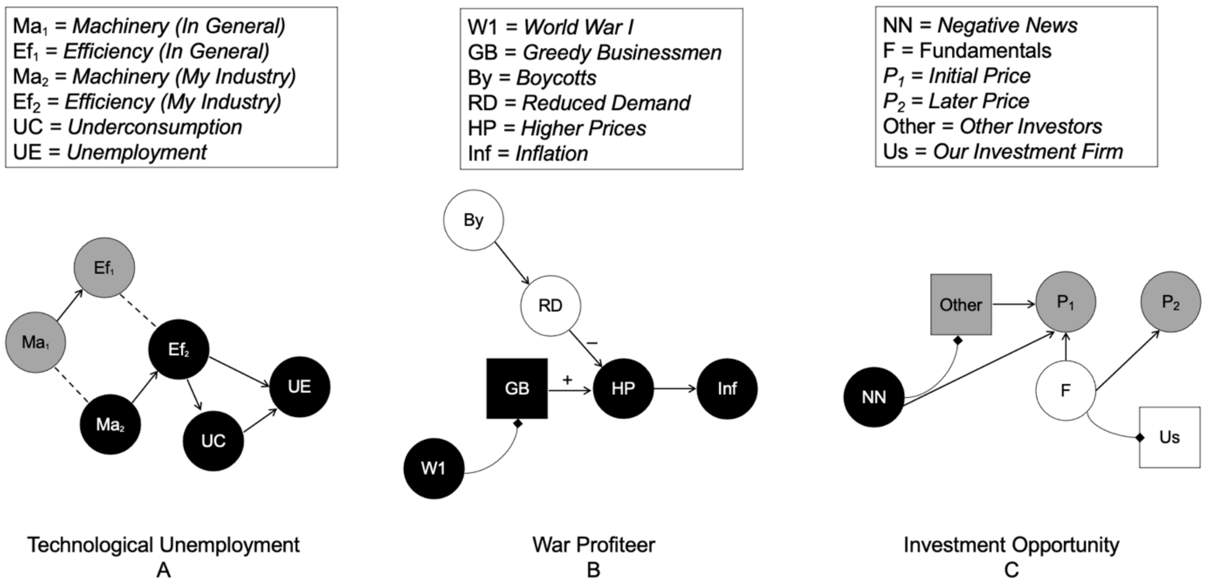

Figure 6. Economic narratives from linguistic and interview data. Panels A–C depict simplified versions of three narratives drawn from Shiller's (2019) linguistic studies of viral economic narratives and Tuckett's (2011) interview studies of money managers. In Panel A, a generic causal mechanism of machinery generally leading to increased efficiency (*Ma*$_1$ and *Ef*$_1$) is analogized to machinery in one's particular industry leading to increased efficiency in that industry (*Ma*$_2$ and *Ef*$_2$). Efficiency is thought to cause unemployment (*UN*) directly by displacing human workers and indirectly through underconsumption (*UC*). Because unemployment is seen as bad, all other variables in the causal chain are inferred to be bad too. In Panel B, greedy businessmen (*GB*) are inspired by the opportunity of World War I (*W1*) to increase prices (*HP*), which leads to inflation (*Inf*). A boycott (*By*) is thought to reduce demand (*RD*), which would in turn push prices back down (negative effect on *HP*). Since inflation and the greedy businessmen who cause it are bad, the countervailing boycott chain is perceived as good. In Panel C, negative news about a company (*NN*) is thought to affect its stock price at an initial time (*P*$_1$), but only the company's fundamentals (*F*) affect its stock price later (*P*$_2$). Other investors (*Other*) are less observant and only act based on the negative news, but our investment firm (*Us*) is more observant and sees the fundamentals, creating a profit opportunity.

He described one stock his firm had bought the previous year (Figure 6c), which had been experiencing issues with a main supplier, leading to very negative news. His team, however, "kicked the tyres and did a lot of work" to conclude that the situation was not so dire as widely perceived, taking a large stake that rose over 50% within weeks. After exiting their position, there were more negative news items, involving a very large shareholder selling the company's stock, causing apprehension in the market and price drop; they again concluded that the company was undervalued and "re-established the position." "It was somewhat controversial…. It was not easy going against consensus sentiment but that's…what distinguishes us." It worked out.[1]

Respondents' narratives coalesced around common themes (Tuckett, 2011, pg. 89). For instance, among the 165 "Buy" narratives from the 2007 interviews, themes included spotting some attractive feature through the respondent's exceptional ability or effort (45% prevalence as rated by independent content-coders); the company/sector offering exceptional opportunities (39%); limits to downward surprise (27%); management as proven and reliable (26%); successful management of the respondent's own emotions (11%); and (temporary) monopoly or market power (10%).

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[1] Excerpts can be found in Tuckett (2012). The full interview, along with the three others selected at random from this larger group, is available at https://www.macmillanihe.com/companion/Tuckett-Minding-The-Markets/study-resources/. More detailed analysis of all the decisions reported by the entire sample, also supported by randomly drawn examples from the coded interview data, has been reported elsewhere (Tuckett, 2011).

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In addition to providing examples of narrative thinking, these interviews illustrate five features of the radically uncertain decision context money managers face, which suggest why narratives are useful (Tuckett, 2011, pgs. 50–54). First, they acted in situations where they could only speculate about the outcome of their actions and doing nothing *was* an action. Second, the financial assets they traded had unknowable future values. Given their mandates to try to outperform each other, they sought opportunities that they thought wrongly priced. To establish mispricing, they imagined how various stories might influence future income streams of a firm and how others would react in those situations. The issue, in the several hundred decisions analyzed, was always the same: How to know and create confidence in their particular story about future prices. Third, the available data to help them form price expectations was effectively infinite—a massive range of public and privately available information, some of questionable provenance, from countless sources in numerous languages. Fourth, they made decisions in a social context. Most respondents talked with or explored their views of the future with others or had to justify their decisions (and reputations) to others. Fifth, decisions were never final and time horizons were always part of the context. For how long would prices go lower before rising? Had prices reached their peak? The money managers' decisions had many of the features depicted in Section 1, which they managed using narratives.

Interviews do not provide conclusive evidence about cognitive processing, but do underscore two key points—the respondents' decision context is characterized by radical uncertainty, and respondents frequently invoke narratives in their reflections on these choices. Plausibly, narratives may have played some role in many of these choices, but finer-grained experimental evidence is needed to understand this role more precisely.

6. Explanation

Good decisions about the future often depend on how we understand the present. *Explanation* is how we create these understandings—how narratives are constructed and evaluated.

We have a fundamental motivation to make sense of things (Chater & Loewenstein, 2016)—a drive that pervades mental life. The world is not perceived directly, but must be interpreted (Fodor & Pylyshyn, 1981; Gregory, 1970; von Helmholtz, 2005/1867). Light hits our two-dimensional retinas, and perception allows us to infer from this a three-dimensional world—to make sense of data under uncertainty. Much cognitive processing has a similar logic: Assembling relevant facts into useful models that can guide predictions and choices. Categories license predictions about individuals, using an object's observed features (evidence) to determine the appropriate category (hypothesis) (Murphy & Medin, 1985). Causal cognition explains events (evidence) in terms of hidden causes (hypotheses) (Lombrozo, 2016). Our memories use scattered strands of remembrance (evidence) to piece together a coherent story about what happened (hypothesis) (Bartlett, 1932; Johnson & Sherman, 1990). Theory-of-mind uses others' observed behavior (evidence) to infer mental states (hypotheses) (Gergely & Csibra, 2003).

Bayesian approaches to explanatory reasoning are popular in both cognitive science and philosophy of science. This approach conceptualizes the phenomenon to be explained (*explanandum*) as evidence and potential explanations as hypotheses to be evaluated using Bayesian inference. Thus, rational explanation requires the reasoner to evaluate the prior probability of each explanation [$P(H)$] and the fit of the evidence with the explanation [$P(E|H)$].

In two important respects, this is a successful theory. First, it uses the same mental machinery to understand many explanatory inferences. There is a common logical structure to explanatory inferences such as causal reasoning, theory-of-mind, and categorization; rather than invoking entirely separate mental mechanisms, it assumes common computational mechanisms. This is in keeping with the empirical evidence as well as theoretically parsimonious. Second, it accounts for why people are reasonably adept at explaining events. Enterprises such as science, technology, and commerce—not to mention everyday activities such a social interaction—depend on explanatory processes; to the extent we are adept at these activities, we are necessarily adept at explaining things.

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Yet this approach cannot be quite right. For the reasons above (Section 2.2.1), such calculations are often impossible in *principle*, much less for flesh-and-blood humans, given aleatory and epistemic limits on probabilities. Bayesian accounts can try to avoid this problem by claiming agnosticism about the actual processes used to reach the outputs of Bayesian theories (retreating to the computational level) or by invoking approximation mechanisms that do not require the full probabilistic machinery. Despite our sympathy with both approaches, the theoretical problems can only be fully resolved if these strategies avoid invoking probabilities altogether under radical uncertainty.

Even eschewing probabilities altogether—as in some Bayesian sampling approaches (Sanborn & Chater, 2016)—cannot avoid a further problem: A dizzying array of empirical anomalies relative to Bayesian predictions. For instance, people often favor explanations that are simpler than merited by the evidence (Lombrozo, 2007), while in other contexts favoring overly complex explanations compared to rational models (Johnson et al., 2014). Although people reasonably prefer explanations that explain more observed evidence (Read & Marcus-Newhall, 1993), they also prefer explanations that make no unverified predictions (Khemlani et al., 2011), contradicting Bayes' theorem. Yet these anomalies are not random: They point to systematic principles we use to evaluate explanations in the absence of precise probabilistic reasoning.

6.1. We use a suite of explanatory heuristics to evaluate narratives

Successful explanation under radical uncertainty requires strategies that circumvent probabilistic reasoning, but instead exploit other forms of structure available in a given situation. People use a variety of heuristics and strategies satisfying this criterion (e.g., Horne et al., 2019; Lombrozo, 2016; Zemla et al., 2017). These strategies are useful, not because they are infallible or optimal (which may not even be meaningful under radical uncertainty), but because they do not require explicit probabilistic reasoning, yet exploit regularities that often make these strategies broadly truth-tracking.

Above, we highlighted how temporal, analogical, and valence information are incorporated into narrative representations. Heuristics exploiting such information are valuable because they capitalize on regularities we naturally attend to, such as event structure and causal mechanisms, while powerfully constraining which explanations are deemed plausible (Einhorn & Hogarth, 1986). For example, people use temporal order (Bramley et al., 2018), the delay between cause and effect (Buehner & May, 2002) and the part–whole structure of events (Johnson & Keil, 2014) to disambiguate causal directionality, determine which events are causally relevant, and assign causal responsibility. Such strategies are adaptive because they exploit regularities in the environment that are less susceptible to the problems of radical uncertainty, even if they are not infallible.

Likewise, analogies allow us to extend hard-won knowledge of one domain into another. Much of our causal knowledge appears to be stored in the format of stereotyped causal schemas (Johnson & Ahn, 2015, 2017). We can analogically reason from a known story (e.g., my cousin's marriage; the Spanish Flu) to the current situation (e.g., my marriage; COVID). Or at a more abstract level, we reason from known causal mechanisms when evaluating an unfamiliar domain, as when we compare the economy to a stalled car or a bureaucratized corporation to an arthritic giant. The notion that "good begets good" (Leiser & Aroch, 2009) can be thought of a highly generalized causal schema, with narratives failing to match this schema (e.g., actions that decrease inflation are likely to increase unemployment) fighting an uphill battle for plausibility. In other cases, we have domain-specific expectations (Johnston et al., 2018), such as the belief that physical causation follows more linear causal pathways compared to the more web-like structure of social causation (Strickland et al., 2016).

Other heuristics derive from causal structure itself, accounting for the anomalies above. People often substitute the vague and challenging question of an explanation's prior probability for the more straightforward question of an explanation's simplicity (Lombrozo, 2007). Yet, because simpler explanations often explain less of the data, people also use an opponent *complexity heuristic* to estimate an explanation's fit to the data or Bayesian likelihood (Johnson, Valenti, & Keil, 2019). Likewise, people prioritize explanations that account for a wider range of observations (Read & Marcus-Newhall, 1993) and attempt to make inferences about evidence that has not actually been observed (Johnson et al., 2016; Khemlani et al., 2011).

Explanatory heuristics are used widely across cognition—for problems such as categorization, causal attribution, theory-of-mind, stereotyping, and even some visual tasks (Johnson, 2016; Johnson et al., 2014, 2015, 2016; Sussman et al., 2014) and emerge early in development (Bonawitz & Lombrozo, 2012; Cimpian & Steinberg, 2014; Johnston et al., 2017). They are also linked to action: People favor explanations that license task-relevant and high-utility actions, and which highlight stable causal relationships likely to apply across contexts (Johnson et al., 2015; Vasilyeva et al., 2017, 2018). Explanatory heuristics, though imperfect, aid people in circumventing specification limits and information limits (Section 2.2.1).

6.2. Explanatory fit is experienced affectively

Although these heuristics may function to push us toward more useful or probable portions of the hypothesis space, their phenomenology is often more affective than cognitive. Emotions rapidly summarize information not readily available to consciousness (Rolls, 2014; Rozin & Fallon, 1987; Todorov, 2008). Because emotions have an intelligence of their own (Nussbaum, 2001), we make inferences from them (Cushman, 2020; Schwarz, 1990) and often rely on "gut" feelings to assess situations (Klein, 1998). This can be a broadly rational strategy despite leading to some mistakes.

In the case of explanations, we feel "satisfied" when we achieve a sense of understanding (Gopnik, 1998; Lipton, 2004). Despite the adaptive basis of many of these heuristics, we do not *feel* like we are performing rational computations when using them. Instead, good explanations often are accompanied by positive emotions or even aesthetic beauty (Johnson & Steinerberger, 2019), as when scientists and mathematicians claim to prioritize beauty in constructing their theories. Conversely, explanations that conflict with prior beliefs produce cognitive dissonance and may therefore be rejected (Festinger, 1962).

Although heuristics often lead to error (Kahneman, 2002), they can be adaptive in solving problems given cognitive and environmental limits (Gigerenzer & Goldstein, 1996; Simon, 1955). Good thing, too: Under radical uncertainty, they often are all we have.

7. Simulation

Having selected a narrative through explanation, we project the narrative into the future through simulation. This is why sense-making and imagination are linked: We make sense of the past to imagine the future.

7.1. Imagined futures are simulated by projecting a narrative forward

The brain mechanisms involved in prospective thought about the future overlap with those used for episodic memory about the past (Schacter et al., 2008) and may even be subsystems of a broader *mental time travel* faculty (Suddendorf & Corbalis, 1997, 2007). This is consistent with our view that the same representations—narratives—underlie explanations of the past and simulations of the future (Aronowitz & Lombrozo, 2020). Moreover, simulation can rely on step-by-step reasoning using causal mechanisms. For example, when shown a set of interlocked gears and asked which direction one gear will turn given that another gear is turned, people solve this problem by mentally turning one gear at a time (Hegarty, 2004). Likewise, thoughts about how reality might be different—counterfactuals—operate over causal structures (Rips, 2010; Sloman, 2005) and are central to imagination (Markman et al., 1993).

However, less work has looked at how particular features of narratives manifest in simulations or how these simulations manifest in choices. Our recent research program has studied the role of narrative-based simulation in financial decision-making.

Our strategy relies on the idea that cognitive processes have specific signatures associated with their limitations or biases. To use an example from a different area (Carey, 2009b), a signature of analog magnitude representations is that the ability to discriminate two magnitudes is proportional to their ratio. Since discriminations for large (but not small) numbers have this property, this implies that representations of large numbers are analog.

Analogously, we look for signature limitations associated with using narrative representations for predictions and decisions under uncertainty. Since narratives can incorporate causal, valence, temporal, and analogical structure (Section 5.1), we designed experiments to examine whether introducing these structural features into forecasting problems produces signature biases relative to standard financial theory. Although any one study does not necessarily implicate narratives, their combination triangulates on the conclusion that people project narratives to simulate the future.

7.1.1. Causal structure: Internal and external attributions. Narratives contain causal structure which provides explanations. Therefore, if people use narratives to forecast the future, causal explanations should affect future forecasts. To test this, participants read about companies that had recently changed in stock price (Johnson, Matiashvili, & Tuckett, 2019a). According to financial theory, the reason for the price change is irrelevant to predicting future prices. For example, when a CEO retires, the firm's stock price often declines. But this decline occurs when the CEO's retirement becomes publicly known, after which it does not reliably produce further declines. Nonetheless, if people use stories to predict the future, it should be irresistible to look for *why* the price changed and use these inferred causes to predict further price changes.

In one study, we compared three explanation types for a price change—no explanation, an internal attribution (relating to skill or quality, e.g., an ill-considered management change), or an external attribution (relating to factors outside the company's control, e.g., a market crash). Participants predicted more extreme future trends when an explanation was given rather than not given, and more extreme trends when the explanation was internal rather than external. This suggests that people look for causal stories to account for events and predict future ones, the most compelling stories invoking internal or inherent features (Cimpian & Steinberg, 2014).

Financial markets are volatile: Prices often shift with little apparent cause (Shiller, 1981). Might people nonetheless supply causes of price changes by default, affecting downstream predictions? To find out, we compared the no-explanation and internal-explanation conditions to a noise condition, in which the price change was explained as random. Several conclusions followed. First, participants still projected more positive trends after a positive (vs. negative) price change, even if told that the change was random: People are "fooled by randomness" (Taleb, 2001; Tversky & Kahneman, 1971), even when randomness is noted explicitly. Second, the no-explanation condition was always more extreme than the noise condition, but less extreme than the internal-explanation condition: People consider unexplained price changes to contain some signal but not as much as explained changes. Third, this effect was asymmetric. For positive changes, the no-explanation was closer to the internal-explanation condition, whereas for negative changes, the no-explanation was closer to the noise condition. Thus, unexplained price changes—accounting for most volatility—are treated more like signal when positive and like noise when negative. This could lead to bubble dynamics, wherein positive price trends build on themselves but the corresponding force in the negative direction is weaker.

7.1.2. Valence structure: Approach and avoidance. Events in narratives often have positive or negative valences, motivating approach or avoidance behavior. To test the effect of valence structure on forecasts, participants read about fictitious companies which experienced either good (an increase in earnings) or bad news (a decrease in new oil discoveries), announced prior to the most recent stock price quotation (Johnson &

Tuckett, 2021). According to financial theory, there is no further effect on the stock price once the information is publicly revealed and priced in. However, if people use narratives to organize their beliefs, they should continue to rely on this valence information to predict future value.

They did. Without news, participants thought that a stock would increase in value by +4.3% in the following two weeks. These predictions were much more extreme when news was available (+10.1% and –5.9% for good vs. bad news). This implies that people believe that markets profoundly underreact to news, leading to price momentum (prices trending in a particular direction). Could participants have intuited the finding that financial markets *do* experience modest price momentum in the short- to medium-term after news announcements, which then reverts back toward the baseline trend (Shefrin, 2002)? If so, they should predict smaller gaps between positive and negative news at longer intervals. In fact, the predicted gap is *larger* at a one-year interval (+16.1% vs. –5.9%). Price expectations seem to follow valenced stories about the companies' underlying causal propensities—with companies categorized as "good" versus "bad"—rather than economic intuition.

7.1.3. Temporal structure: Asymmetries between past and future. Narratives also contain temporal structure, which implies a boundary condition on the effect of valence: When information is related to the future (vs. the past), we should see more of an effect of its valence on predictions. Indeed, consistent with CNT but not standard financial theory, news about the future (e.g., a revision to next quarter's projected earnings; +17.5% predicted one-year change) stimulated more extreme predictions compared to news about the past (e.g., a revision to last quarter's actual earnings; +14.7%). Thus, not only the valence but also the temporal orientation of news affects forecasts, in line with narrative representations (Johnson & Tuckett, 2021).

Moreover, the valence- and time-based predictions described in Sections 7.1.2 and 7.1.3 manifested in emotions—more positive forecasts led to more approach emotions, more negative forecasts to more avoidance emotions—which in turn motivated investment decisions. This confirms a basic principle of CNT: People use narratives to imagine the future, react affectively to that future, and choose in line with their affect (Section 8.1).

7.1.4. Analogical structure: Pattern detection and extrapolation. Analogies allow us to impose structure on problems by using our knowledge of one thing to understand another. Although some analogies compare radically different things (e.g., an atom is like the solar system), most analogies are much more prosaic: This dishwasher is like that dishwasher, this dog behaves like other dogs, this company's future resembles that other company's.

Our minds seem to hold multiple, conflicting analogies which can impose structure on time-series price data. On the one hand, it seems plausible that a series of prices trending in one direction should continue that trend—*momentum*. Many familiar variables have this property—successful people tend to become even more successful; objects in motion tends to stay in motion (as in the analogy of 'momentum' itself). At the same time, it seems equally plausible that if prices have trended one way, it's only a matter of time before the trend reverses—*mean reversion*. Mean reversion too is common among familiar variables—extreme weather regresses toward the mean; objects thrown into the air come down eventually. The extent of momentum and mean reversion in real prices has been a matter of great debate in behavioral finance. Given that people can harness sophisticated intuitions for pattern detection and extrapolation (Bott & Heit, 2004; DeLosh et al., 1997), how might we resolve these conflicting analogical intuitions when predicting future prices?

We anticipated that these analogies are triggered by different evidence, with these analogical frames imposed on time-series data to best explain it and project that explanation into the future. This signature bias would contrast with standard financial theory, which says that only the current price and its variance (risk) are relevant to future prices, as well as with existing behavioral models which assume that people are linear trend extrapolators (Barberis et al., 2015).

In our studies, participants encountered prices series in one of three patterns (Johnson, Matiashvili, & Tuckett, 2019b). In the *linear* condition, the prices had been trending in either a positive or negative direction for 5 periods. Here, participants linearly extrapolate the trend, consistent with past work (Cutler et al., 1991; De Bondt, 1993; Hommes, 2011; Jegadeesh & Titman, 1993). But in two other conditions, we find strikingly different results. In the *reversion* condition, prices had previously experienced a reversion during the past 5 periods—they had the same starting price, ending price, and mean as the linear condition, but experienced higher variance in the intervening periods. Participants had a greatly dampened tendency to project this trend linearly, with many believing that prices would reverse again. In the *stable* condition, prices had previously hovered around one price level before experiencing a sudden increase or decrease to the current price. This pattern too led many to predict reversion, toward the previously stable price.

These results suggest that people draw on analogies—such as momentum and mean reversion in other data series—to generate narratives to account for past price trends, projecting these narratives to forecast the future. We find similar pattern-based expectations for many other consumer and investment prices, and real stock prices in an incentive-compatible task. Beyond their theoretical implications, these results may be economically significant, as price expectations play key roles in asset pricing (Hommes et al., 2005) and inflation (Carlson & Parkin, 1975).

7.2. Imagined futures are simulated one at a time

We have focused so far on how narratives circumvent limitations on probabilistic thinking. Yet narrative thinking has limits of its own: Once we have adopted a particular narrative, we are often blind to alternative possibilities. We simulate narratives one at a time.

For example, different government policies lead to different predictions about market prices. If the central bank raises interest rates, this is likely to depress market prices. But central bankers often speak opaquely. If an investor assigns a 75% chance to the story that the banker plans to raise rates but a 25% chance to the story that the banker plans to leave them alone, does she account for both possibilities or rely on just one? A Bayesian would calculate the likely effect on markets if each story is true, taking a weighted average when estimating future prices. But an investor who "digitizes" and treats these stories as either certainly true or false would "round up" the 75% chance to 100% and "round down" the 25% chance to 0%. Only the dominant narrative resulting from explanatory reasoning would be retained for downstream computations such as forecasting.

We found that investors are not Bayesians, instead digitizing (Johnson & Hill, 2017). In one study, participants were given information leading them to think that one government policy was likelier than another (in one variation, they were even given these probabilities directly). Comparing conditions identical except the effect of the more-likely (75% chance) policy, there was a large difference in predictions. But comparing conditions identical except the effect of the less-likely (25% chance) policy, predictions do not differ at all. Investors take account of the implications of more-likely narratives, but ignore entirely the implications of less-likely narratives: They adopt a single narrative as true, treating it as certain rather than probable.

Digitization is a broad feature of cognition; similar effects have been found in causal reasoning (Doherty et al., 1996; Fernbach et al., 2010; Johnson et al., 2020) and categorization (Lagnado & Shanks, 2003; Murphy & Ross, 1994). Yet it has boundary conditions: People do reason across multiple hypotheses in cases where one of the hypotheses invokes a moral violation (Johnson, Murphy, Rodrigues, & Keil, 2019) or danger (Zhu & Murphy, 2013), and expertise in a domain may promote multiple-hypothesis use (Hayes & Chen, 2008).

Despite boundary conditions, simulations produce, by default, a single imagined future. Electrons may exist as probability clouds rather than in one definite state. But stories resist Heisenberg's principle—they take only one state at a time.

8. Affective Evaluation

We have seen how narratives solve the mediation problem: They summarize available data (about the past) in a format used to predict what will happen (in the future) given a particular choice. But choices must somehow combine these visions of the future with our values and goals—the combination problem. Since emotions function to coordinate goals, plans, and actions (Damasio, 1994; Elliot, 2006; Fishbach & Dhar, 2007; Ford, 1992; Lewin, 1935; Oatley & Johnson-Laird, 1987; Rolls, 2014), *affective evaluation* is tasked with solving the combination problem.

Let's first consider how existing theories of emotion address simpler choices. Suppose someone cuts into the supermarket queue and you must decide whether to assert your rightful place. According to the *appraisal-tendency framework* (Lerner & Keltner, 2000), the decision-maker evaluates this situation along several dimensions—including certainty, pleasantness, controllability, and others' responsibility—which jointly determine which emotion is felt (Smith & Ellsworth, 1985). In the queue-cutting case, one might perceive the event as unpleasant and the queue-cutter as responsible, but the situation as certain and under control—leading to anger. Or instead, one might be less sure that the queue-cutter acted deliberately but perceive the situation as less controllable and certain because the queue-cutter appears big and mean—leading to fear. These emotions, in turn, motivate different actions (Frijda, 1988); anger is an approach emotion motivating aggression, whereas fear is an avoidance emotion motivating withdrawal. Finally, once these emotions are active, they shift attention to relevant dimensions for subsequent events; for example, fear leads one to perceive subsequent events as relatively uncontrollable compared to anger (Lerner & Keltner, 2001).

CNT adds three modifications to account for challenges in complex, future-oriented decision-making. First, emotions are felt not only in response to actual events but to *imagined futures* generated from narratives, motivating us to approach or avoid associated choices. Second, appraisals of those futures can rely either on a default set of dimensions or on ad hoc evaluations relative to specific goals. Finally, since decisions must often be sustained over time, feelings of conviction in a narrative permit committed action in the face of uncertainty.

8.1. Affective evaluations of imagined futures motivate choices

We feel emotions in response not only to the present situation, but to situations we imagine (Loewenstein et al., 2001; Richard et al., 1996). This is why we experience emotions when understanding literature (Mar et al., 2010) or empathizing with others (Mitchell et al., 2005). CNT accords a central role to the emotional reactions we experience in response to imagined futures generated from narratives. These emotional reactions *within* a narrative, by motivating approach and avoidance behaviors, drive action in the real world.

Some emotions are inherently future-oriented: If one feels excited (or anxious) about a potential future, one acts to approach (or avoid) that future. But even past-oriented emotions, such as regret (Loomes & Sugden, 1982), can influence our choices through simulations of how we would feel. For example, people anticipate more regret over not playing in postcode lotteries (where non-players can learn if they would have won) versus traditional lotteries, which motivates participation (Zeelenberg & Pieters, 2004). Many other anticipated emotions are known to guide choices, including guilt, sadness, anger (Baron, 1992); pleasure (Wilson & Gilbert, 2005); dread and savoring (Dawson & Johnson, 2021; Loewenstein, 1987); and envy (Loewenstein et al., 1989). Emotions mediate between our predictions of the future and decisions to approach or avoid that future, coloring narratives with emotion (Beach, 1998; Bruner, 1986).

8.2. Imagined futures can be appraised on default or ad hoc dimensions

The fuzzy evaluation problem (Section 2.2.2) results from the challenges of summarizing incommensurable attributes as a single utility, especially when our values may change over time. CNT proposes two computational simplification strategies that the affective system can use to address this problem—a default, bottom-up strategy and an ad hoc, top-down strategy.

This is analogous to the distinction between natural categories and ad hoc categories. Natural categories—such as BIRD, TABLE, and MOUNTAIN—roughly capture regularities in the external world (Rosch et al., 1976); by default, objects are classified bottom-up, automatically and effortlessly, into natural categories (Greene & Fei-Fei, 2014). In contrast, ad hoc categories (Barsalou, 1983)—such as THINGS TO SELL IN A GARAGE SALE and WAYS TO ESCAPE THE MAFIA—are constructed on the fly to achieve specific goals, using effortful, top-down processes. Whereas bottom-up classification into natural categories proceeds by default and relies on predetermined dimensions, top-down classification into ad hoc categories requires effort and relies on spontaneously determined, goal-derived dimensions.

Analogously, in line with the appraisal tendency framework, one strategy for evaluating imagined futures relies on a default set of dimensions mirroring those for evaluating actually present situations (e.g., controllability, certainty, pleasantness), which determine which emotion is felt. That emotion, in turn, motivates action. Because these dimensions are thought to be evaluated automatically with minimal effort (Lazarus, 1991), this default appraisal strategy is an appealing solution to the fuzzy evaluation problem. Specific emotions are felt in response to qualitative appraisals of predetermined dimensions. Because the dimensions are predetermined, the computational problem of identifying dimensions is avoided; because the appraisals are qualitative, the need to trade off these dimensions is circumvented. Moreover, although particular preferences may well change over time, our basic emotional architecture does not. Thus, the problems of incommensurable attributes and non-stationary values are averted.

However, these default dimensions often do not suffice when we have specific goals, leading to a second, ad hoc strategy based on the decision-maker's goal hierarchy. A decision-maker's attention will be deployed according to the active goal(s) at the time of decision-making (van Osselaer & Janiszewsi, 2012). Narratives can be used to generate imagined futures, on an ad hoc basis, that are evaluable with respect to these goals. The compatibility of those imagined futures with those goals produces approach and avoidance emotions that motivate action (Elliot, 2006; Oatley & Johnson-Laird, 1987).

This ad hoc route depends on two claims. First, we assume that although we may have many goals, a small subset are typically active at once, because goals are triggered context-dependently (Panksepp, 1998; Tuckett, in press) and organized hierarchically. For example, when basic physiological needs are not met, these are likely to supersede less immediately essential needs such as social belonging (Lavoie, 1994; Maslow, 1943). This is not only helpful for survival, but also a crucial computational simplification: Goal hierarchies allow us to evaluate imagined futures over a much smaller number of dimensions. This is how ad hoc appraisals, like default appraisals, help to resolve the fuzzy evaluation puzzle. This insight also casts new light on multi-attribute choice strategies (Payne et al., 1988). A couple facing divorce faces a dizzying array of potential attributes. Yet, for many such couples, their children's well-being is paramount. If this dimension does not prove decisive, they may move on to other concerns, such as their financial well-being or sexual satisfaction. The hierarchical organization of goals can explain why particular situations call for particular decision rules, such as lexicographic rules (using a single attribute) or elimination-by-aspects (eliminating options beneath a minimum criterion on a key attribute, then iteratively considering other dimensions; Tversky, 1972).

Second, we assume that we can generate imagined futures containing details relevant to evaluating the required dimensions. For example, our married couple might first imagine their future with respect to their child's well-being, then elaborate this image to consider their romantic prospects, then their finances. Although these different imagined aspects may well emanate from a shared narrative of the couple's married life, it is unlikely that this complete conception of their future would emerge fully-formed, but instead must be simulated one piece at a time. Although we do not know of any research directly examining this proposed

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ability in the context of narratives, evidence about other domains suggests that this is possible; for example, people can fluidly reclassify objects dependent on goals (Barsalou, 1983) and can manipulate their mental images dependent on queries (Kosslyn, 1975).

8.3. Emotions are used to manage decisions extended over time

Hamlet's uncertainty paralyzed him for three acts; by the fifth act, it was too late. Hamlet learned the hard way that strong, conflicting arguments produce ambivalence that can stop action in its tracks (Armitage & Conner, 2000; Festinger, 1962; Rosner et al., 2022; Rucker et al., 2014; Smelser, 1998). Many a couple and many an investor have talked themselves in circles while romantic and financial opportunities slipped away; committing to one distinct course of action often yields better fortunes, even if one can never be certain a choice is truly "right." Moreover, high-stakes decisions often are extended through time, requiring commitment. Failure in this respect leads many novice investors to overtrade and defray their gains through transaction costs (Barber & Odean, 2000). Conviction bears dividends.

Yet, conviction also bears risks. Blindly following a plan, while ignoring new information, is equally a recipe for disaster as Hamletian paralysis. Complex problems such as the COVID pandemic, Putin's Ukraine invasion, or climate change require different approaches as events or our knowledge evolve. Emotions are instrumental in the inter-related processes of *conviction management*—*gaining conviction* (acting in the face of ambivalence), *maintaining conviction* (committing to a sustained course of action), and *moderating conviction* (taking account of new evidence and potentially changing course as the situation changes). To manage conviction is to manage our emotional attachments to a person, object, or course of action. A lack of emotional attachment against the temporary vicissitudes of fortune yields indecision, yet an inability to reappraise a truly changing situation can yield calamity.

Cognition and affect are intertwined in generating conviction. Conviction-generating narratives integrate information about the past and expectations about the future to emotionally support a course of action. Experiments have probed this process. In a purely cognitive model, confidence in a decision is proportional to the strength of the arguments in its favor; in a purely affective model, confidence in a decision is proportional to its propensity to trigger approach emotions. Instead, cognition and emotion work together (Bilovich et al., 2020). When situations trigger approach emotions, investors find favorable arguments more relevant, with the converse for avoidance emotions. Perceived relevance in turn influences investors' choices. Although emotions profoundly affect choice, they do so by influencing intermediate cognitive processing.

This interplay between cognition and affect is also illustrated by the conviction-generating strategies cited by the investment managers in Tuckett's (2011) interview study (Chong & Tuckett, 2015). Numerous respondents (90%) referred to one or more 'attractor' narratives, producing excitement over an investment due to an exceptional opportunity for gain. Attractor narratives typically cite either the investment's intrinsic properties (e.g., exceptional products) or the investor's own special skills (e.g., exceptional insight). A similar proportion of respondents (88%) referred to one or more 'doubt-repelling' narratives, reducing anxiety over an investment. Doubt-repelling narratives typically raise and then counter a potential concern, placing bounds on either uncertainty (e.g., competent managers) or downside surprise (e.g., solid fundamentals).

Uncertainty can undermine conviction, but so can excessive certainty in dynamic situations. At a single time-point, people are more confident in investments described as having a specific, predictable return (8%) rather than falling within a range (3% to 13%) (Batteux et al., 2020; Du & Budescu, 2005). However, building conviction by masking uncertainty is not sustainable: Once point forecasts are shown to be unreliable—an inevitable event under uncertainty—trust is reduced in the forecaster (Batteux et al., 2021a). This has implications for risk communication: When uncertainty is communicated in vaccine announcements, trust in vaccines is buffered against subsequent negative outcomes (Batteux et al., 2021b).

Conviction is not good or bad in itself. It is needed to overcome ambivalence and sustain commitment, but is only adaptive if it does not preclude learning. When emotions are regulated well (Gross, 1998), conviction buffers against the vicissitudes of the unfolding situation, but can be moderated. In such an *integrated state*, we can be sensitive to new information and adjust decisions in an orderly way; one adopts a particular narrative but acknowledges the possibility of error and stays attuned to evidence for competing narratives. In contrast, in a *divided state*, ambivalence is hidden by attentional neglect of information inconsistent with the preferred narrative. Whereas new information in integrated states can trigger curiosity and evidence integration, incongruent information is rejected in a divided state (Tuckett, 2011; Tuckett & Taffler, 2008). This is why ambivalence has been linked both to maladaptive responses, such as confirmation bias and behavioral paralysis, and adaptive responses, such as broader attention and willingness to consider multiple perspectives (Rothman et al., 2017). Decision-makers who experience balanced emotions are likelier to rely on "wise reasoning" strategies, such as epistemic humility and integrating diverse perspectives (Grossmann et al., 2019). Integrated conviction management is adaptive because it permits decision-makers to accept a narrative as provisionally true and act accordingly—a crucial characteristic when there is a cost to changing course—while accumulating evidence in the background, changing course when clearly merited.

Integrated conviction management is closely linked with one way that feedback loops help decisions to become adaptive over time. Although under radical uncertainty we often have no choice but to make some decision without a clear sense of whether it is best option, we can accumulate evidence about what does and does not work. Thus, *acting on* one narrative can yield information that is then used to *reappraise* that same narrative, potentially leading to a shift in narrative and decision in an iterative manner. Extended decisions can often be treated as a series of experiments, providing information about what does and does not work (Fenton O'Creevy & Tuckett, in press).

9. Communication

Many everyday decisions are inseparable from their social context. The *communication* processes through which narratives or narrative fragments are transmitted across minds are crucial for understanding decision-making at macro scales. Subjecting narratives to cultural evolution has allowed narratives to adapt over time to generate reasonably high-quality decisions in the absence of calculable probabilities and utilities.

9.1. Shared narratives facilitate social coordination

Decisions are socially embedded in part through their shared consequences—when decisions are taken collectively, as in political decision-making, or when one individual's decision affects others in their social group. Socially coordinated decisions can generate more value than the sum of their individual components (Chwe, 2003). However, coordination is challenging, due to both divergent interests and divergent information. Shared narratives help to coordinate both interests and information.

Reputation-tracking is key to aligning individual incentives with collective interest (Rand & Nowak, 2013; Tennie et al., 2020). People are motivated to evaluate others' reputation based on their actions, even actions only affecting third-parties. For instance, people evaluate others' moral character based on prosocial actions such as donation (Glazer & Konrad, 1996; Johnson, 2020), volunteering (Johnson & Park, 2021), and eco-friendly actions (Griskevicius et al., 2010), generating incentives for apparent altruism. Conversely, bad reputations are costly: People sacrifice resources to punish free-riders (Jordan et al., 2016). Because we are aware that others are tracking our reputations, we are motivated to take actions bringing reputational benefits and avoid actions bringing reputational harm.

An important means for reputation management is how we justify choices to others (Lerner & Tetlock, 1999; Mercier & Sperber, 2017). Narratives often play this justificatory role, maintaining reputation in the face of disagreement and coordinating group activity when other stakeholders must adopt the same decision. For instance, stories shared by the Agta, hunter–gatherers in the Philippines, express messages promoting cooperation, allowing skilled storytellers to achieve greater cooperation (Smith et al., 2017). Closer to home, scientists often debate what "story" they will sell to readers and reviewers. Why are narratives so effective for reputation maintenance?

First, narratives contain causal structure that can generate *reasons* justifying a position. For example, when deciding which parent should be awarded custody of a child, people favor the parent with both more extreme positive (above-average income) and negative attributes (work-related travel) over one with more neutral attributes (typical income and working hours), since the former gives more positive reasons favoring custody. But when asked instead who should be *denied* custody, people again choose the more extreme parent because there are also more *negative* reasons *against* custody (Shafir et al., 1993). More extreme attributes support more causally potent explanations, generating both supporting and opposing narratives.

Second, narratives can not only justify decisions after the fact but to *persuade* others to adopt our perspective (Krause & Rucker, 2020). Arguments communicated with a narrative are often more persuasive than those communicated with facts alone (Chang, 2008; De Wit et al., 2008; Shen et al., 2014), in part because narratives are readily understood (Section 9.2). Narratives induce emotional engagement, mental imagery, and attention, creating "narrative transportation" that can lead reasoners to believe elements of the story (Adaval & Wyer, 1998; Escalas, 2004; Green & Brock, 2000; Hamby et al., 2017; Van Laer et al., 2014). Moreover, the broader narratives espoused by a communicator, such as moral and political worldviews, can lend additional credence to their claims (Johnson, Rodrigues, & Tuckett, 2021; Marks et al., 2019). Persuasion is crucial in coordination because it allows a group to have the *same* narrative in their heads, making narratives a part of our collective or transactive memory (Boyd, 2009; Chwe, 2001; Hirst et al., 2018; Wegner, 1987) and providing a shared plan for coordinated action.

9.2. Shared narratives shape social learning and evolve

Decision-making is also socially embedded through the informational environment. Human knowledge arises largely through our cumulative cultural heritage (Boyd et al., 2011; Henrich, 2018). Indeed, because it is so often the ability to access external knowledge when needed that is crucial for decision-making rather than our internal knowledge itself, we often confuse knowledge inside and outside our heads (Sloman & Fernbach, 2017).

Communication of narratives is a crucial way we learn beyond immediate experience (Boyd, 2018), with some even suggesting that the adaptive advantage of sharing narratives is the main reason that language evolved (Donald, 1991). However, we do not suggest that narratives in the full form described in Section 5 migrate wholesale from one mind to another. The knowledge that is transferred from one mind and stored in another is relatively skeletal, or even a placeholder (Rozenblit & Keil, 2002) as when we store the *source* of a piece of information rather than the information itself (Sloman & Fernbach, 2017; Sparrow et al., 2011). Instead of full narrative representations, we assume instead that primitive elements—narrative fragments such as basic causal schemas, memorable analogies, and emotional color—are the key narrative elements that are shared and shape social learning. These narrative fragments, communicated consistently within a social group, give rise to a set of elements that are common among the narratives represented within those group members' individual minds—what we are calling a *shared narrative*.

Several approaches seek to model how ideas spread and evolve (Boyd & Richerson, 1985; Dawkins, 1976; Sperber, 1996). A common insight is that ideas spread when they pass through two sets of cognitive filters: Constraints on encoding (attention, memory, and trust) and constraints on communication (motivation and ability to share). But for a culturally transmitted idea to not only spread but be *acted on*, that idea must pass through a third filter—constraints on action. The idea must be perceived as actionable and produce motivation to act. Narratives can pass through all three filters—encoding, communication, and action—and therefore are likely to socially propagate.

First, narratives are easy to remember. People often represent information as scripts, or stereotyped sequences of events (Schank & Abelson, 1977). Because people so naturally represent information using causal–temporal structure, people are far better at remembering information organized as stories (Bartlett, 1932; Kintsch et al., 1977; Thorndyke, 1977). Humans' remarkable ability to remember information encoded as stories is perhaps most impressively attested by oral traditions, such as the transmission of the Greek epics and Hindu and Buddhist historical texts over centuries purely through word-of-mouth (Rubin, 1995).

Second, people like to talk about narratives, making them susceptible to spreading through word-of-mouth (Berger, 2013). This may be because narratives are well-suited to balancing novelty against comprehensibility (Berlyne, 1960; Silvia, 2008), with the most contagious narratives including a small number of novel concepts against a larger background of familiar concepts (Norenzayan et al., 2006). Narratives can convey new information in digestible form because they match our default causal–temporal representations of events (Schank & Abelson, 1977) and focus on the behavior of human actors, commandeering our natural tendency toward gossip (Dunbar, 1996). Moreover, as discussed above, narratives are highly persuasive, and therefore commonly used when trying to convince others.

Finally, narratives lend themselves to action. Because narratives have a causal–temporal organization, and are often organized around the actions of individuals (Mandler & Johnson, 1977), they provide a ready template for intervening on the world. Indeed, causal knowledge is crucial precisely because it can be used to bring about desired outcomes (Woodward, 2003). Culturally acquired knowledge of physical causation is embedded in physical tools, which can manipulate the physical world. Analogously, culturally acquired knowledge of social causation is embedded in narratives, which serve as templates for manipulating the social world. We suggest that narratives which lead to *effective* actions are particularly likely to survive this filter, just as effective institutions are likelier to survive social evolution (Hayek, 1958). Therefore, narratives that have survived this crucible of cultural evolution potentially lead to adaptive decision-making even under radical uncertainty.

Because narratives live and die by cultural evolution (Boyd & Richerson, 1985; Henrich, 2018), their propagation depends on their social, economic, and physical environment. Narratives surrounding masks at the start of the COVID-19 differed profoundly across countries (Hahn & Bhadun, 2021), due both to social norms and differing experience with infectious disease. Henrich's (2020) account of how the West became prosperous suggests that narratives originated by the Catholic Church altered norms around cousin marriage, generating new family structures and patterns of cooperation that led to markets and science.

9.3. Shared narratives propagate through social networks

If shared narratives facilitate coordination and learning, then as they shift over time and propagate through social networks, they should be tied to large-scale outcomes. Since economic actors' decisions are driven by narratives (Section 5.2.2), changes in the emotional content of socially available narratives may shift attitudes toward risk. If so, then measures of approach and avoidance emotions in economic narratives should predict the direction of economic aggregates—output, employment, GDP growth—that depend on investment. Nyman et al. (2021) studied this claim using text-mining techniques on internal Bank of England commentary (2000–2010), broker research reports (2010–2013), and Reuters news articles (1996–2014).

First, relative sentiment is a leading indicator of economic volatility and consumer sentiment. This reflects the idea that a preponderance of approach over avoidance emotions is needed to produce conviction to invest (Keynes, 1936). For each document, the proportion of words signaling approach (e.g., "excited," "ideal") and avoidance words ("threatening," "eroding") was calculated, with the difference between these indices constituting *relative sentiment*. Shocks to relative sentiment in the UK had negative effects on industrial production, employment, and the stock market, with these impacts lasting for nearly 20 months (Nyman et al., 2021). Tuckett and Nyman (2018) also found that relative sentiment also predicted changes in investment and employment in the UK, US, and Canada more than 12 months out (Tuckett, 2017). For example, a plot of relative sentiment against major events in the lead-up to the global financial crisis shows a precipitous decline in relative sentiment in the year leading up to the failure of Bear Sterns in March 2008. A similar analysis using 1920s data from the *Wall Street Journal* found that sentiment shocks, beyond economic fundamentals, impacted production and stock values leading up to the Great Depression (Kabiri et al., 2022); sentiment likewise appears to account for the slow recovery from the 2008 recession (Carlin & Soskice, 2018).

Second, excessive homogeneity around narratives portends trouble. Nyman et al. (2021) used topic modeling to assign each article in the text database to a particular narrative and compute the degree of narrative topic consensus at each time point. Prior to the crisis, homogeneity increased around narratives high in approach emotions (excitement) and lacking avoidance emotions (anxiety), which could have been a potential warning sign of impending financial system distress (Nyman et al., 2021). This supports the idea of groupfeel or emotional conformity as a driver of booms and busts and the notion that integrated emotional states that manage ambivalence are better-suited to stable decision-making, compared to divided states that ignore discordant information (Tuckett & Taffler, 2008).

Macroeconomic crises are necessarily rare and atypical, so no method will reveal definitive answers about their causes. But these techniques can also be used at a more micro-scale. For example, Tuckett et al. (2014) studied relative sentiment in news articles about Fannie Mae. From 2005 to mid-2007, sentiment became increasingly exuberant, along with Fannie Mae's share price, and unmoored from economic realities reflected in the Case-Shiller Housing Price index. Such states can result from the fetishization of some "phantastic object" (Tuckett & Taffler, 2008)—in this case, mortgage securitization. A similar analysis of Enron's internal emails in 2000–2002 revealed comparable emotional–narrative dynamics of build-up and collapse surrounding the deregulation of the California energy market and Enron's impending (ill-fated) entry into broadband. Overall, the confluence of macro- and micro-level analyses converges to suggest that emotional–narrative sentiment spreads through social networks and may causally influence economic outcomes.

10. Conclusion

So often, decisions in economics textbooks and psychology experiments alike are divorced from the need for sense-making and imagination, overtly quantified in their consequences and probabilities, taken at a single timepoint, and stripped of social context. This reductionist tradition has yielded massive progress. But progress in understanding everyday decision-making also requires us to put back those elements that have been stripped away. CNT is our answer to this need.

To summarize CNT standing on one foot: *We impose narrative structure on information to explain the past, imagine the future, appraise that future, take sustained action, and coordinate actions socially.* The mediation problem—a mental representation that can mediate between the external world and our choices—is solved by narratives; the combination problem—a mental process that can drive action by combining beliefs and values—is solved by emotion. Decisions can be reasonably adaptive even without well-specified probabilities and utilities because individual narratives are influenced by culturally evolved shared narratives and by feedback from our own actions.

10.1 Meta-Theoretical Considerations

Scientific theories, like narratives, are evaluated partly on aesthetic grounds. In this spirit, we discuss two potential 'meta-theoretical' objections to CNT.

First, some may view CNT as too *grandiose*. Philosophers have mostly given up on generating grand unified theories, and similar efforts such as behaviorism have fared little better in psychology. A skeptical reader may view CNT as a kaleidoscope of ideas—encompassing narratives, explanation, causation, analogy, forecasting, emotion, motivation, cultural evolution, and more—biting off too much theoretical meat to properly chew, much less digest.

Second, some may view CNT as too *skeletal*. We do not provide our own account of explanation or emotion or cultural evolution, but rather focus on how these processes fit together. Even the notion of narratives—the theoretical centerpiece of our account, as the mental substrate binding these processes—can be elusive, as it coordinates lower-level representations of causation, analogy, time, and valence. Perhaps we have not bitten off theoretical meat at all, but merely bones.

We are sympathetic to these concerns. Yet we believe that in this case, we have encountered a grand problem that *requires* a strong skeleton. CNT is not grand in the sense that it attempts to explain all of cognition; rather, it is attempting to explain decision-making under radical uncertainty—an important problem that has largely resisted theoretical progress. It is a grand problem precisely *because*, we contend, many parts of our mind cooperate to make such decisions. Approaches that ignore any component piece will lack the theoretical machinery required to understand the problem. If CNT is grand, it is not by choice but by necessity.

Thus, CNT is *not* a theory of explanation, analogy, causation, or emotion, but a theory of *decision-making under radical uncertainty*. We focus less on the details of these component processes because it is how the processes *interact* that is central to how we produce the conviction to act under uncertainty. We do not necessarily take a side where there is theoretical disagreement about one of these processes; rather, we specify how these processes relate *to each other*. CNT is skeletal because the skeleton *is* the theory; the meat, though delicious, belongs to other theories.

10.2 Contributions

We are not the first to highlight the importance of narratives to decision-making, nor (we hope!) the last. But we have aimed to provide an integrative framework that allows insights from several disciplines to be combined, contributing to the ongoing conversation in four main ways.

First, by explaining in detail how narrative decision-making works. We provide a representational framework that captures key information used in real-world examples of narrative-based decisions, and explain how these representations sustain processes of explanation, simulation, and affective evaluation, which jointly motivate action.

Second, by highlighting that narratives address important puzzles about everyday decision-making. Many ordinary decisions are plagued by radical uncertainty, fuzzy evaluation, and the need for sustained commitment; they involve sense-making and imagination; they are inextricably linked to social context. Such decisions—where optimality is ill-defined—resist dichotimization into 'rational' versus 'irrational'. Narratives not only help to solve these problems, but often do so adaptively. Feedback loops at both the individual level (managing conviction for decisions sustained over time) and the collective level (the cultural evolution of narratives) contribute to adaptive choice.

Third, by identifying how processes ordinarily studied in isolation work together. Recent advances in explanatory reasoning highlight the role of heuristics and affect in explanation under radical uncertainty—advances unknown at the time of Pennington and Hastie's (1986) seminal work. Causal and analogical processing have been studied extensively, with excellent cognitive models of each; yet these models have been integrated surprisingly little with one another or with decision-making models. The pivotal role of affect in solving the fuzzy evaluation problem has received less than its deserved attention in the decision-making literature, as has the role of cultural evolution in socially propagating narratives that can then guide individual choices. We hope to put these areas in dialogue.

Finally, by providing a common vocabulary—including our ideas around the structure of narrative representations, the information flow among narrative processes, and the set of problems to be addressed by a theory of everyday choice.

In keeping with this final point, we emphasize that a common vocabulary is needed precisely because CNT will not be the final word on this topic. Indeed, some of our proposals remain tentative even for us. First, although we believe that causal, temporal, analogical, and valence structure are the key lower-level information included in narratives, there may be other forms of information we have not considered. Second, relatively little is known about how these kinds of information are coordinated; thus, our proposals around narrative coherence rules must remain tentative and likely incomplete. Third, although much has recently been learned about explanatory heuristics, we have not provided an exhaustive list of these heuristics but merely given a few examples to illustrate how they work; more will surely be discovered. Fourth, we know relatively little about what specific features of narratives lead them to be more or less socially contagious and which of those features promote adaptive decisions; memes are selfish, as Dawkins (1976) noted, and not all features of catchy narratives are likely to be adaptive. Yet we would add that the preoccupation of much decision-making research with optimality—whether in assumption or subversion—might profitably yield some ground to the more basic question of how, under radical uncertainty and fuzzy evaluation, we gain conviction to act at all.

We are excited by the prospect that CNT might provide a fruitful platform for collaboration between researchers across the decision sciences—a rallying cry for all who aim to understand social, psychological, and economic aspects of decision-making in the real world.

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