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DISCUSSION PAPER SERIES

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# ABSTRACT

## Entrepreneurs: Clueless, Biased, Poor Heuristics, or Bayesian Machines?*

Entrepreneurship scholars are interested in understanding and describing how entrepreneurs make decisions under uncertainty, where the probabilities of outcomes are not known but perceived, resulting in ambiguous probabilities. In this context, ambiguity refers to the lack of precise and objective probability assessments and the presence of subjective judgments regarding potential outcomes. In this chapter, we discuss the development of thought on how entrepreneurs perceive and react to uncertainty from Frank Knight (1921) to the present day. Recognizing that entrepreneurs face uncertainty rather than risk and are unlikely to have estimates of all probabilities for all potential outcomes, it becomes difficult to accept Expected Utility Theory (EUT), developed by Savage (1951) and von Neumann and Morgenstern (1953), as a relevant model for entrepreneurial decision-making. We examine a range of decision theories, ranking them in an order starting from EUT and proceeding to the most structure-free models of entrepreneurial choice, allowing for comparisons and contrasts of the main components and underlying concepts as they apply to entrepreneurial decision making.

**JEL Classification:** L26, J24

**Keywords:** entrepreneurship, uncertainty, ambiguity, decision theory, Bayesian Entrepreneurship

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# Introduction

First order of business is to introduce some definitions of terms. There are three core elements of decision making (Fischhoff & Broomell, 2020): a) judgment, or how people predict the outcomes that will follow possible choices. This can be evaluated in terms of the accuracy of judged probabilities or by their consistency. The most familiar consistency standard is Bayesian inference. Biases distort judgment; b) preference, or how people weigh those outcomes. Decision theorists allow individuals to have any preferences, but have a consistency standard: preferences must satisfy the utility theory axioms; and c) choice, or how people combine judgments and preferences to reach a decision. This is about the model used to put everything together, and we review a few of these models in this Chapter, among which several do not satisfy the utility theory axioms. Heuristics mainly distort choices.[1]

Starting from the left in Figure 1, one could use EUT to describe how entrepreneurs *should* choose which action to take. EUT is not a descriptive theory but a normative theory, prescribing how an entrepreneur should use information to rank order all options to choose the optimal option under risk. EUT contains a number of axioms that, if fulfilled, allow the decision maker—the entrepreneur in this case—to rationally choose the best action that, on average (in expectation), delivers the most favored outcome. However, this model's ability to describe decision-making has faced various objections (see, for instance, Starmer, 2000), too numerous to list here. The most problematic aspect of its application in entrepreneurship is that the entrepreneurial decision situation does not meet EUT's data requirements, such as having access to the probabilities of outcomes associated with all alternative options. Entrepreneurial decision-making fundamentally

[1] In this chapter, we use the term heuristic as a cognitively less demanding and faster alternative to EUT, which may however lead to suboptimal decisions. The term heuristic is sometimes also used to describe a shortcut in the formation of beliefs. A deeper review of the foundations and the state of the art of the literature of judgment and decision making can be found in Fischhoff and Broomell (2020).

revolves around uncertainty (McMullen & Shepherd, 2006; Townsend et al., 2018), where probabilities of future states, such as market demand or technological opportunities, are unknown (Knight, 1921). Consequently, entrepreneurial scholars have rejected the EUT framework.[2]

However, if this model is rejected, there remains a need for frameworks that help entrepreneurship scholars better understand how entrepreneurs make decisions and assist entrepreneurs in choosing the best possible action among a set of alternatives. Hence, to meet the demands for realism, decision theory researchers have developed alternative theories that address some of the violations of EUT. In addition, these theories describe situations where probabilities are characterized as unknown but subjectively assessable (i.e., ambiguous), or even more radically, where potential future states and outcomes are not knowable by the decision maker. In the former case, one can still compare the subjective values of different actions if one can assign self-assessed subjective probabilities for various future states. In the latter case, there are two types of theories to discuss: those in which the entrepreneur is unable to rank order any sets of actions and stands in front of complete (also called absolute) uncertainty, and those in which the entrepreneur is partially able to rank order some but not all potential choices. Finally, an (extreme) alternative would be to completely reject the notion that entrepreneurs evaluate the chances and values of outcomes when making decisions. This is the case of effectuation theory, developed by Sarasvarthy (2001), which stands at the opposite end of the spectrum of the theories we will review. We have picked to review a few prominent theories, and a few forgotten, but in our minds highly relevant alternatives to help understand entrepreneurial choices.

Entrepreneurship scholars now stand armed with a range of alternative theories of entrepreneurial judgment and decision-making under uncertainty. Few of these alternative theories of

[2] Other optimization models such as Minimax, where a pessimist chooses the option that minimize the possible loss for the worst-case scenario, or Maximax, where an optimist chooses the option which makes possible the maximum payoff, do not suffer from the same deficit as EUT being that the probabilities of outcomes associated with all alternative options must be known.

entrepreneurship have been tested. Only a handful of empirical entrepreneurship studies have expanded beyond risk to behavior under ambiguity, using variants of the famous Ellsberg's (1961) urns task (e.g., Holm et al., 2013; Koudstaal et al., 2016), or have examined decision biases associated with uncertainty. We only sparsely review the empirical testing of these theories, saving that review for another time. Finally, at the end of this Chapter, we will place Bayesian Entrepreneurship on the scale in Figure 1, which summarizes the various theories.

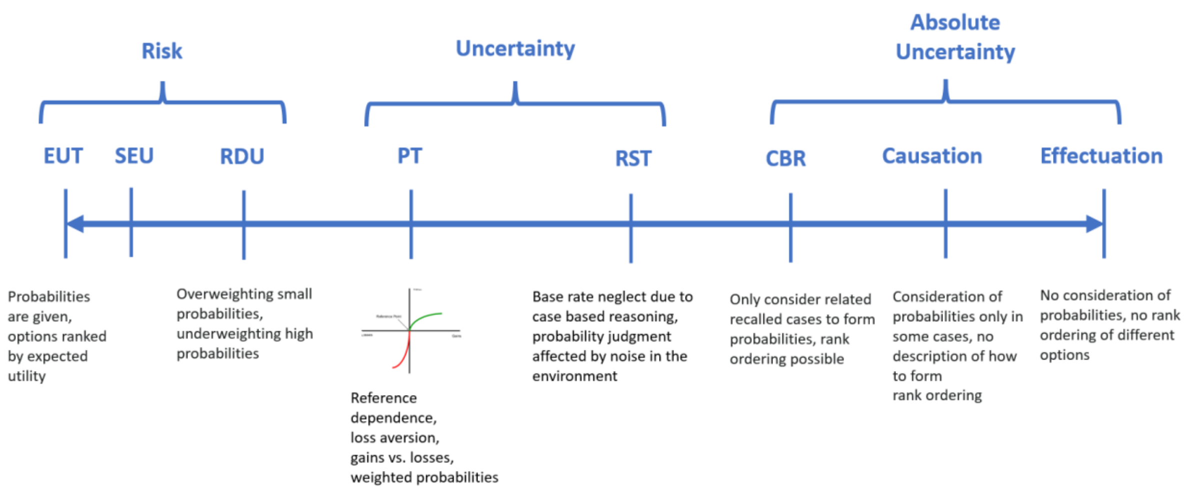


**Figure 1. Theories of (entrepreneurial) probability judgment and decision under risk, uncertainty, and absolute uncertainty.** *Notes*: Picture credits to Daniel Chen. EUT: Expected Utility Theory; SEU: Subjective Expected Utility; RDU: Rank Dependent Utility; PT: Prospect Theory; RST: Random Support Theory; CBR: Case-Based Reasoning.

# Expected Utility Theory

Starting with EUT, it is, again, important to clarify that EUT is not a descriptive theory but a normative one. It does not aim to describe how individuals usually make decisions. Instead, it specifies the conditions under which the best action can be selected among a range of alternatives. Other theories either modify the conditions of EUT to move the conditions closer to descriptive realism, or reject the idea that entrepreneurs need to evaluate choices among alternatives, and instead propose completely new models.

A central tenet in EUT is risk aversion. Entrepreneurship researchers showed an early interest in examining the hypothesis that entrepreneurs are more willing to take risks than others (Kihlstrom & Laffont, 1979). Brockhaus (1980) is one example, where no differences were detected between entrepreneurs and the population at large. Other articles include Cramer et al. (2002), Caliendo et al. (2009), Ahn (2010), and Skriabikova et al. (2014). Åstebro et al. (2014) reviewed the accumulated evidence and found that the differences in risk aversion that were detected between employees and entrepreneurs cannot fully explain why individuals choose to become entrepreneurs.[3]

Frank Knight (1921) told us so. He stated that we should not think of entrepreneurship as simply investment under risk, where decisions are made with respect to an objectively known distribution of returns. He argued that entrepreneurship in such a world would not require any particular skill, and it would be inconceivable that entrepreneurs could earn rents simply for bearing objective risk as the market should eliminate those rents. Knight therefore argued that the prerequisites for entrepreneurial activity are a combination of highly uncertain returns, which do not have an objectively known distribution, and the entrepreneur's skill in perceiving an opportunity more clearly than others. His work focused attention on the specific individuals pursuing

[3] More subtle definitions of risk aversion such as in the "Need for Achievement" construct, where entrepreneurs strive for situations with a moderate achievement goal and take calculated risks, are then likely even more difficult to distinguish, as they involve even more complex functional forms of risk aversion to estimate. For reviews of the n-ACH construct in entrepreneurship see Johnson (1990) and Stewart and Roth (2007). Judging by these reviews, after being quite popular in research between 1965 and 1985, the construct seems to have waned considerably in popularity, probably partly because of its impreciseness.

entrepreneurship and what made them distinct, as well as the fact that in entrepreneurship the probabilities of outcomes are unknown.

In terms of technical (formal) models of uncertainty versus risk, several recent articles have shown that it really does make a difference how uncertainty is interpreted. Suppose for a moment that "uncertainty" about labor market conditions has increased. Does this induce an individual to search for an entrepreneurial opportunity longer or shorter? In the traditional way to represent uncertainty as risk, where probabilities of outcomes are known, an increase in uncertainty means an increase in the variance of the distribution of entrepreneurial returns around a given mean. A person will then search longer for a higher return, because the upside opportunity just increased. However, a person who interprets the news to mean that there is a decrease in her confidence about which earnings distribution among a set of distributions is the true one, will instead search for a shorter duration and accept a lower entrepreneurial opportunity earlier (Nishimura & Ozaki, 2004).

Savage (1954) extended EUT to situations where no objective probabilities are available. Under Subjective Expected Utility (SEU), objective probabilities are replaced with 'subjective probabilities', meaning that individuals can form opinions, consciously or not, about the likelihood of events. While offering a more flexible model adapted to situations of ambiguity, SEU maintains the normative foundation of EUT.

# Rank Dependent Utility

Decision analysts started to recognize a discrepancy between the normative EUT model and the empirical findings on human decision-making behavior. This search for deviations developed into a storm, fueled most prominently by the work of Daniel Kahneman and Amos Tversky, and their followers, who took it upon themselves to show through numerous small-scale experiments that various inconsistencies with EUT occurred. These inconsistencies, exemplified by the famous 'Allais Paradox' (1953), were not merely noisy decisions but consistent deviations from EUT. We will describe only some of these deviations below as they pertain to their discussion in entrepreneurship. In this subsection, we describe attempts by theorists to incorporate some of these violations of EUT into a formal model that still allows for the rank ordering of alternative options.

Rank Dependent Utility (RDU) was developed to explain why people choose to invest in insurance while also buying lottery tickets. These joint decisions are inconsistent with EUT, as they imply risk aversion in the former case and risk loving in the latter. To reconcile these choices within a utility framework, Quiggin (1982) developed a first version of RDU, which was a major breakthrough in decision theory. The main idea of this model is that "the attention given to an outcome depends not only on the probability of the outcome but also on the favorability of the outcome in comparison to the other possible outcomes" (Diecidue & Wakker, 2001, page 284). In RDU, outcomes are first rank ordered from highest to lowest value. Instead of being weighted by their objective or subjective probabilities, as in EUT or SEU, outcomes are weighted by decision weights that depend on both the probabilities of the events and their ranks among all possible alternatives. The weighting function, which maps probabilities to decision weights, captures the degree of local (i.e., for a certain probability level) risk aversion or risk seeking and is specific to a decision maker.[4] A common finding in the empirical literature is that this weighting function often has an inverse-S shape: individuals tend to overweight unlikely extreme outcomes, such as disasters and winning the lottery, but overweight less, or underweight, more common events. This idea later formed one of the central features of cumulative prospect theory (often referred to simply

[4] The literature often interprets the shape of the weighting function in terms of 'optimism' and 'pessimism'.

as Prospect Theory, or PT) in addition to the incorporation of decision making under uncertainty (Tversky & Kahneman, 1992).

Why is RDU relevant to entrepreneurship? It turns out that RDU can rationalize why entrepreneurs are insensitive to changes in likelihood over a large range of probabilities of outcomes, focusing instead on extremely lucrative or, alternatively, disastrous, outcomes. Verbal representations of this behavior are legion in entrepreneurship, and such narratives have also crept into entrepreneurship theories of various kinds. We may for example refer here to the case of Zappos, recounted in Agrawal et al. (this volume). In a lab experiment, Laferrière et al. (2023) found that the inverse-S shape of the weighting function can partially explain excess entry in winner-take-all markets, which leads to the skewed distribution of returns in entrepreneurship (Åstebro et al., 2014).

# Prospect Theory

Prospect Theory (PT), developed by Daniel Kahneman and Amos Tversky, was created to explain systematic deviations from EUT observed in a series of experiments. In 1979, Kahneman and Tversky introduced the first version of PT that they revised in 1992 to extend and refine the original theory, reflect additional research findings, and relabel some of the concepts (Tversky & Kahneman, 1992).

The main components of Prospect Theory (1979 and 1992 versions combined) are:

a) Reference dependence. Reference dependence implies that what matters is changes to an earnings position from a *reference point*, not changes in final wealth. Reference dependence also implies that context matters, as the reference point could change across context.[5]

b) Loss aversion: the disutility of losses is higher than the utility of gains. In other words, losses loom larger than gains.

c) Utility of gains and losses: the utility function is concave for gains and convex for losses.

d) Probability weighting: Probabilities are transformed into decision weights (as in RDU), but can be weighted differently for gains and losses.

The end goal was to construct a model that describes how the decision maker rank orders different choices. In parallel to constructing the theory, Kahneman and Tversky discussed a list of biases related to probability *judgment*, defined as the formation of beliefs about the likelihood of events, but did not formally include them in the theory that focuses on the *evaluation* of uncertain options. The discussed biases include base rate neglect (i.e., ignoring population-level information) and ordering effects (i.e., taking into account when information is presented). The biases in belief formation were left to a pre-decision "framing" state, before the evaluation and decision. In this framing state, decision-makers might decide to discard very unlikely outcomes, focus exclusively on recent decisions or information, make reference to decision situations that the case "represents", or invoke case-based reasoning or base rate neglect.[6]

Two important updates were made in the 1992 version of PT. First, to resolve a technical issue present in the initial version, the authors incorporated rank-dependence. Second, they extended PT to incorporate decision-making under uncertainty. Although Tversky and Kahneman were not

[5] Kahneman and Tversky wrote: "More generally, the preference order between prospects need not be invariant across contexts, because the same offered prospect could be edited in different ways depending on the context in which it appears" (1979, page 275).
[6] Note the similarities here to theories of entrepreneurial decision making presented by Packard et al. (2017) and Sarasvathy (2001).

the first to develop a model for decisions under uncertainty, they advanced the understanding of how uncertainty may be treated differently from risk. The key insight was that decision weights became “source dependent”, meaning they depended on the context of the decision-making process. Hence, in situations of uncertainty, the decision weights could differ from those in contexts of risk and also vary across uncertain decision contexts. Each decision maker would still have their own weighting function of probabilities, but the weights would be adjusted based on the uncertainty of the data generation process.

Tversky and Kahneman had little empirical evidence when proposing this idea and suggested that “the investigation of decision weights for uncertain events emerges as a promising domain for future research” (1992, p. 317). Abdellaoui et al. (2011) later developed the source method to quantitatively analyze source dependence and found empirical evidence supporting it. In the field of entrepreneurship, Gutierrez et al. (2020) applied the source method to analyze excess entry in markets characterized by uncertain payoffs and skill-based competition, highlighting the critical role of attitudes toward uncertainty beyond mere beliefs. These results align with Wu and Knott (2006)’s finding of “apparent risk seeking” in the case of ability uncertainty. However, Wu and Knott attributed this pattern to entrepreneurs' overconfidence in their own skills.

Even though there is empirical evidence of violations of PT (see e.g. Fox et al., 2015), prospect theory remains one of the most popular theories of decision under uncertainty in terms of its descriptive power, with applications to a broad range of fields (e.g., Barberis, 2013).

# Biases, Preferences, and Heuristics in Entrepreneurship

The three theories previously introduced (EUT, RDU, and PT) are theories of decision-making that focus on choices but do not address the formation of beliefs. In other words, they take the probabilities (objective or subjective) as input to the decision model. Hence, they can help explain the behavior of an entrepreneur *conditional* on holding certain beliefs but do not explain how these probabilities are derived or formed in the first place.

However, in the 1980s, interest in the field of entrepreneurship shifted towards concepts associated with probability judgment, such as optimism and overconfidence, an interest which we briefly review below. These concepts align with Knight's view of entrepreneurs as having unique skills in assessing venture opportunities.

Optimism reflects that all perceived probabilities of positive outcomes are more favorable than objectively measured probabilities. Overconfidence is the exaggerated belief in one's own skills and abilities, often in relation to others, or an excessive faith that you know the truth (see e.g. Moore & Cain, 2007; Moore & Healy, 2008). Optimism is considered a relatively stable personality trait, while overconfidence is more situational. Both have been found associated with entrepreneurship (see Åstebro et al., 2014). More optimistic or overconfident individuals would tend to overvalue the future returns of an entrepreneurial venture. This overvaluation will only affect those that are at the margin of switching, i.e., those who are almost indifferent between becoming an entrepreneur or not; therefore, the overvaluation will bring in a group of marginal performers (see e.g. Dell'Era et al., 2023).

Surveys illustrate the prevalence of inaccurate beliefs among entrepreneurs. For instance, Cooper et al. (1988) reported that 33 percent of surveyed entrepreneurs rated their odds of success at 10 out of 10, despite giving much lower odds to similar businesses. Shane (2009) showed US entrepreneurs' estimated odds of achieving at least $10 million in sales to be five times higher than empirical data suggests. Whether these survey results reflect overconfidence or optimism is unclear. De Meza et al. (2019) showed that optimism caused lower entrepreneurial earnings due to an increased rate of erroneous entrepreneurial entry. Holm et al. (2013) found that Chinese entrepreneurs were more willing to enter competitive environments reliant on their own skills compared to a control group, suggesting a possible link between overconfidence and entrepreneurial entry. However, the entrepreneurs did not consistently overestimate their performance, indicating that a preference for competition might drive their actions more than biased self-beliefs. Åstebro et al. (2014) highlighted the need for more precise measurement of probability assessment in entrepreneurial contexts to better understand the role of overconfidence and optimism in driving the relationship with entrepreneurship.

Another stream of literature shifted from examining tolerance for risk to exploring tolerance for ambiguity, a concept more closely associated with Knight's perspective. Already in 1951, Frenkel-Brunswick proposed that "tolerance of ambiguity" is a stable and broad predictive variable across a number of behavioral settings. Among its many instantiations, she proposed a resistance to the reversal of responses to apparent fluctuating stimuli, and the early selection and maintenance of one solution in an ambiguous situation. Instead, a person with a high tolerance for ambiguity would perceive ambiguous situations as desirable, challenging and interesting. Sexton and Bowman (1985) extended these ideas by comparing entrepreneurship students with other types of students, finding that entrepreneurship students had a greater tolerance for ambiguity. However, their results have not held up well when studying entrepreneurs. Furnham and Marks (2013, page 718) note that "despite work on these subtly different and related concepts there is still no very clear operational definition of Tolerance for Ambiguity at the facet level or a clear differentiation between the manifestations and correlates of Tolerance for Ambiguity". Maybe due to its conceptual unclarity, the construct has not persisted to be used in the field of entrepreneurship. Nevertheless, the idea that an entrepreneur's actions may not respond much to differences in perceived probabilities has survived, and has even had a resurgence, as will be described.

While biases and preferences have received some coverage in entrepreneurship, the use of heuristics by entrepreneurs has obtained very little attention. For two examples, see Åstebro and Elhedhli, (2006) and Busenitz and Barney (1997).

# Random Support Theory

In contrast to EUT, RDU, and PT, Random Support Theory (Brenner, 1995, 2003), or RST, is a theory of probability judgment rather than decision-making. It has been used in conjunction with decision theories that instead focus on choices but do not address the formation of beliefs (e.g., Fox & Tversky, 1998). This approach of separating the probability judgment and action phases is similar to Foss and Klein's beliefs-actions-results framework (2012, 2020).

RST predicts how people assess probabilities in systematically biased ways based on two ideas: a) humans typically apply case-based reasoning; and b) the noisiness of the decision environment affects how individuals assign subjective probabilities. Using examples and small experiments, Kahneman and Tversky (1973, 1979; Tversky & Kahnemann, 1974, 1983) came to believe that intuitive judgments and predictions tend to be driven primarily by characteristics of the specific case at hand (i.e. the entrepreneurial project) and tend to neglect characteristics of the broader class or category to which the specific case belongs (e.g., B2C chatbots). The focus on case-specific characteristics and neglect of class-based aggregate properties then leads to predictable judgmental biases, including base-rate neglect (Tversky & Kahnemann, 1974).

Calibration plots, which compare subjective probabilities to objective ones, illustrate these biases (see Figure 2 for an illustration). Perfect calibration would align on the identity line, but overestimation results in a curve below the identity line, while overly extreme judgments yield a flatter curve. These plots have become the workhorse of decision analysts' attempts at trying to understand how and why individuals perceive probabilities in certain ways.

For example, a perfectly flat line would mean that the entrepreneur does not take probabilities into consideration. RST uses the notion of case-based intuitive judgment to predict systematic miscalibration (Brenner, 1995, 2003). It has parameters that are interpretable as reflecting (in)sensitivity to important class-based characteristics (Koehler, Brenner, & Griffin, 2002; Brenner, Griffin, & Koehler, 2006). RST predicts a flatter calibration curve when an entrepreneur is less able to make causal links between characteristics of the venture and its success. This is how many scholars in entrepreneurship think about uncertainty. For example, it may be more difficult to know exactly how to design the business model to be successful when environmental (or technological) uncertainty is high, such as for startups using large language models or hydrogen-driven automobiles. Entrepreneurs pursuing these ventures are then predicted to tend to ignore information about the class as a whole, such as the base rate of success, and focus on the project at hand, leading to a flatter calibration curve. For another class of ventures, such as restaurants, the business model is considerably clearer, the secrets to success are more tangible, and the general success rate is better known. As the level of noise about cause-effect relations and the base rates vary across classes of ventures, so will the calibration plots vary in predictable ways. This theory rests on the idea that decision makers are more sensitive to the case at hand than on class-based information, and specifically models how uncertainty in the decision environment affects the bias in judgments.

In studies using judges in the Canadian Innovation Center's Inventors Assessment Program, (Åstebro & Elhedhli, 2006; Åstebro & Koehler, 2007) the authors found support for this theory in the field. The judges were asked to assess the commercial opportunity of inventions and provide recommendations to the inventor on whether the invention is worth pursuing further. Lacking probability base rates to make comparisons against, judges rely on their internal library of past reviews, pick out a couple of cases that seem similar and proceeds to make case-based comparisons, similar to what Kahneman and Tversky described in their early experiments (Kahneman & Tversky, 1973, 1979; Tversky & Kahnemann, 1974, 1983). Even though the judges are adept at separating between extreme cases, their evaluation process invites some well known decision biases, such as base rate neglect and overextremity.

We reproduce the main result in Figure 2 below. The two graphs show the calibration plots, mapping judges' subjective probabilities to objective ones. The dashed line is parameter-free while the solid line presents a 2-parametric RST model. The 45 degree angle represents perfect calibration of beliefs. The results show that there is, relatively speaking, higher correlation between assessed cues and outcomes when there is lower uncertainty (left graph). The right graph, on the other hand, shows the judges' assessments when there is high unpredictability about the outcomes based on the assessed cues information for another class of inventions. There is more overextremity (a flatter curve) in this situation as predicted by the theory.

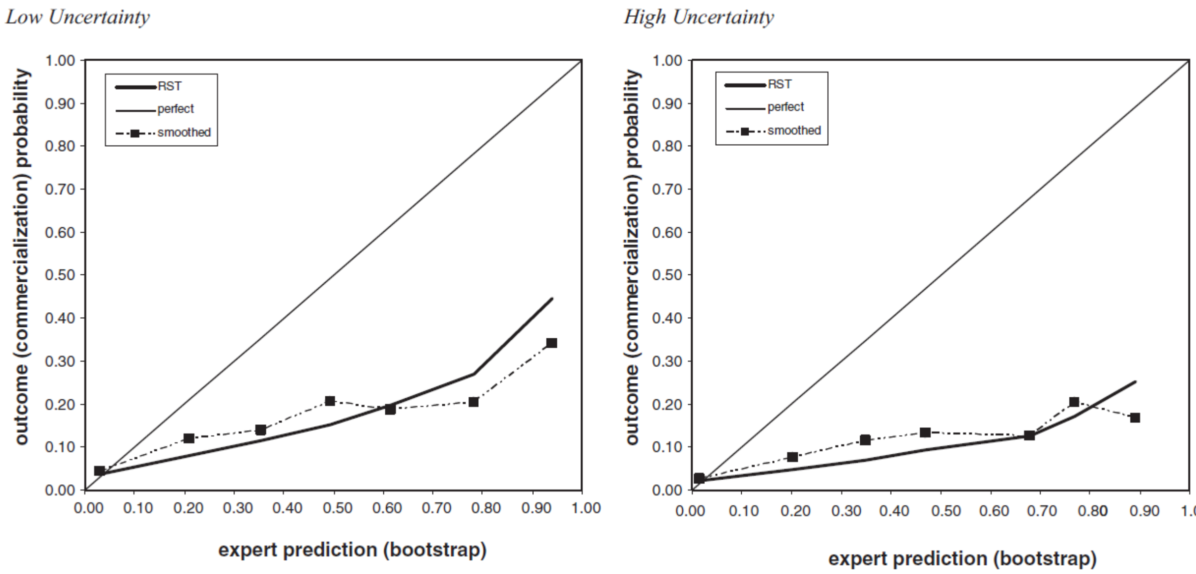


**Figure 2. Calibration of probabilities under low and high uncertainty in entrepreneurship.**

*Source*: Åstebro and Koehler (2007). Copyright: John Wiley & Sons, Ltd. Reproduced with permission. *Note*: RST stands for Random Support Theory. The calibration plots show correspondence between an expert prediction of commercialization probability derived from a model correlating decision criteria with judgment, and the actual probability of commercialization ("smoothed") for low and high uncertainty inventions. Fit of RST model to each calibration curve is also shown.

# Case-Based Reasoning

Case-Based Reasoning (CBR) is a formal theory of decision-making under uncertainty, where probabilities are unknown or belong to a set of probability distributions, or where only some probabilities can be deduced. It therefore belongs to the classes of models under absolute uncertainty. In CBR, the decision-maker does not have knowledge of future 'states of the world', their probabilities, or outcomes, and can only vaguely attribute cause-and-effect relationships since future states are unknown (Gilboa & Schmeidler, 1995).[7]

A key idea in CBR is that the decision-maker recalls a few past cases and makes inferences about what might happen if a similar action is taken in the current situation. This is therefore a model that tries to define the origin of beliefs of decision makers who do not have complete information. It is an alternative to EUT and SEU when both states of the world and probabilities are neither given nor can be easily constructed, and therefore belongs to theories of absolute uncertainty. This modeling approach accommodates a number of biases related to belief formation highlighted by Tversky and Kahneman (1974), while at the same time, the model also prescribes the best mode of action among a limited set of options, but, crucially, these options are not derived from "looking into the future". CBR can further explain behavioral patterns such as satisficing, or incorporate concepts such as aspiration levels, both of which have attracted considerable attention in theories and descriptions of decision making (e.g. Simon, 2013; Cyert & March, 2015).

Further model developments and clarifying arguments followed (e.g. Gilboa and Schmeidler, 2000), explaining that CBR suggests that people make decisions by analogies to past cases: they tend to choose acts that performed well in the past in similar situations, and to avoid acts that performed poorly. The decision-maker only needs to recall a few cases, and which cases are recalled may be influenced by biases such as an over-reliance on salient or recent cases (see e.g. Tversky & Kahneman, 1974).

[7] Preceding this model were models of decision making under uncertainty that retain the classical state-space approach as in Gilboa (1987), Gilboa & Schmeidler (1989) and Schmeidler (1989). These models retained generalizations of Subjective EUT to deal with unknown probabilities (but potentially known, and at least explicitly modeled states of the world). None of these models deals with the question of the origin of preferences, which is the key point of CBR.

From this limited set of recalled cases, the decision-maker infers potential outcomes if she takes a similar action for the case at hand, i.e., the current entrepreneurial project, as for those recalled from experience. Not all recalled cases have the same weight on the decision. A "similarity function" describes how related the recalled cases are to the current case, and decision makers weigh the outcomes of each recalled case by their similarity with the current case. Recalled cases do not have to be 'real' but can also be hypothetical or counterfactual. CBR retains the formalism to evaluate and rank order different actions but may be considered closer to the realities of decision making for entrepreneurs and their advisors. It has similarities to the verbal model of "effectuation" (Sarasvarthy, 2001), which will be described later, as both assume that the decision-maker is not able to discern the future states of the world, but instead build up perceptions based on past experiences. CBR is an astute formal model of entrepreneurial reasoning that deserves more attention from the scholarly field of entrepreneurship.

## Decision under Absolute Uncertainty

There is not yet any agreement in the entrepreneurship literature on how to describe probability judgment and decision-making under absolute uncertainty, where possible states of the world and events are unknown, and where there are no or very weak causal links between actions and outcomes (see e.g. Packard et al., 2017). For some theorists, it seems implausible that entrepreneurs can come up with a rank order of actions under such conditions. Decision making in this world may therefore be characterized as making random choices or at least choices unaffected by any form of evaluation of alternatives. Or, as suggested by CBR, choices rely on past experiences plus analogous thinking. To make things more concrete, consider the theory of effectuation. In this theory, the potential entrepreneur behaves like a cook rummaging through the kitchen cabinet to create a meal from whatever ingredients are available. The focus of this theory is not the analysis of the decision situation but how to take action using limited means (Sarasvarthy, 2001). It is therefore a boundary case where there is no (or sparse) structure in the evaluation of alternative actions. The key limiting factor in this theory is resource constraints, where the chef, in this example, is fully constrained and cannot go on a shopping spree to create the most delicious (and computed to be the most profitable) meal to sell. Instead, the chef must settle for a meal that is sellable at some lower profit, given the resources at hand. This does not mean that the decision-maker does not evaluate alternative meals given what is in the cupboard, but that she operates under binding constraints.

Other authors, such as Packard et al. (2017), have tried to relate “effectuation” and other verbal descriptions of entrepreneurial decision making to Knight’s characterization of entrepreneurs making judgment and decisions under absolute uncertainty. Packard et al. (2017) distinguish between open and closed sets of decision options, and open or closed sets of outcomes, creating a 2 by 2 typology of different decision environments. Under absolute uncertainty, both sets are open and the prospective entrepreneurs have to decide on what set to close first to make a decision. The authors propose that effectuation and causation are two paths to reduce the absolute uncertainty to what they call a “perceived opportunity”. In their view, effectuation involves taking the set of options as given and immutable (thus closed), being a function of a fixed set of endowed resources, and then trying to figure out what the outcomes will be for each option, without (much) evaluation of their chances of occurrence. In contrast, causation starts by closing the set of possible outcomes, without necessarily considering the available options, before evaluating what options to take. How the outcomes are evaluated in relation to their chances of occurrence is not made precise. It seems that this theory of causation under absolute uncertainty primarily describes the editing stage of PT where information is collated, or where there is a selection of cases to refer to as sources of relevant comparisons, as in RST or CBR. None of the theories of PT, RST or CBR are very precise in how these cases are conceived. PT only obliquely encapsulates how information is collated, although there is certainly a long list of decision biases that affects how information is collated and edited.[8] CBR addresses how past experiences affect future decisions head on, but does not explain why certain experiences are recalled and others not. The ideas presented in Packard et al. (2017) in a verbal way then give more flavor to this process of imagination and unpacking of options, while not paying much attention to how probabilities or values of outcomes are later mentally estimated and combined to form a decision.

Yet other authors focus on the process of belief formation in the context of uncertainty and how that leads to action (e.g. McMullen and Shepherd, 2006; Shepherd et al., 2007). These authors make a distinction between a generally observable third-person entrepreneurial opportunity and a first-person opportunity that a specific person may observe and act upon. The actionable opportunity is a function of, for example, individual-specific knowledge. The framework in these theories is not dissimilar to that of PT, RST or CBR, as it starts with the supposition that there are potential links between cause and effect that can be observed by some, and that these decision-making parameters are different for different people based on their past experiences and their ability to recall them.

## Bayesian Entrepreneurship

In addition to the different models presented earlier, a recent literature advocates for training entrepreneurs to think more systematically and scientifically about information gathering, making

[8] The reader might be amused scrolling through (two of many) lists at https://en.wikipedia.org/wiki/List_of_cognitive_biases and https://thedecisionlab.com/biases.

choices, and taking actions. This literature is summarized in this book as reflecting the entrepreneur as a Bayesian updater.

A theory has begun to be formed about Bayesian entrepreneurs. In this framework, the entrepreneur starts with a prior belief about the probability of success, performs a well-structured experiment based on a theory-driven hypothesis, collects the data, and forms a posterior belief about the probability of success (Agrawal et al., this volume). With this process, these entrepreneurs are said to progress from *ex ante* opaqueness to *ex post* clarity about the value of business opportunities, to ultimately form a subjective probability distribution treating uncertainty in a way similar to risk (Zellweger & Zenger, 2023, p. 362). Entrepreneurs can then rank order options and choose the most preferred one. Other chapters in this volume describe this approach in more detail. A series of randomized controlled experiments have demonstrated that entrepreneurs can be taught to form a theory about an entrepreneurial opportunity, design an experiment to test it, and gather relevant information to identify the most promising path forward (Camuffo et al., 2020; 2023; 2024; Coali et al., 2024).

From the perspective of this Chapter, the theory of Bayesian Entrepreneurship is positioned as a version of Subjective Expected Utility. It emphasizes the formation and updating of beliefs through subjective probabilities. Over time, these subjective probabilities become more accurate as the entrepreneur gains experience and improves calibration. Essentially, the theory explains how entrepreneurs should form and adjust their beliefs, thereby making more informed decisions based on evolving subjective probabilities. The authors of this Chapter would then expect the entrepreneur to still have perceived probabilities that do not exactly fall on the identity line of the calibration plot. More generally, based on our current understanding, we would like to clarify Bayesian Entrepreneurship, to the best of our ability, from the perspective of decision theory. We understand the theory to have the following main components: 1. Subjective probabilities;

2. Optimistic beliefs; 3. Initially faulty heuristics; 4. Decisions that are malleable through scientific training; and 5. Training that offers better heuristics.

We now discuss these components of the theory. The Bayesian Entrepreneurship theory provides a valuable lens through which to understand entrepreneurial decision-making. However, like every theory, it has some limitations. One limitation of the Bayesian Entrepreneurship theory, derived from the assumptions of SEU (point 1 above), is its reliance on the independence axiom. A substantial body of empirical literature, beginning with the well-known 'Allais Paradox' (1953), demonstrates that this axiom is often violated. This has given rise to several behavioral decision theories, many of which we have discussed in various sections of this Chapter. Another critical assumption of SEU is probabilistic sophistication across sources of uncertainty, which posits that only subjective probabilities matter when evaluating ambiguous events, irrespective of the source of uncertainty. The Ellsberg paradox and subsequent literature highlight violations of this assumption. People generally exhibit non-neutral attitudes towards ambiguity, treating risk and ambiguity differently.

The Bayesian Entrepreneurship theory also takes a positive view on the role that 'strong priors' play in entrepreneurial decision-making (point 2 above). For example, in the case of the online shoe retail startup Zappos, the founder is said to be specifically optimistic about the success chances of the business idea as he held beliefs that were contrary to the mainstream, driving him to experiment with a business model that others dismissed (Agrawal et al., this volume). However, this focus of Bayesian Entrepreneurship theory on the founder's evaluation of likelihood of success may miss alternative explanations for the entrepreneur's actions, for example different attitudes to ambiguity, different mental rules and strategies, or different repositories of experiences.

The impact of these limitations depends on whether the theory aims to be descriptive or normative. From a descriptive standpoint, failing to account for violations of the independence axiom or probabilistic sophistication can reduce the theory's explanatory power. Failing to account for heuristics and decision biases also ignores a long tradition of research showing their power in affecting judgment and decisions. These could maybe be assumed to fall into the error term as well, but this is perhaps a strong assumption since biases and heuristics typically do not lead to random deviations from the true mean, but predictable deviations. Normatively, the issue is more complex. For instance, there remains an ongoing debate about whether ambiguity neutrality should be considered normative. Some authors advocate for a normative approach to ambiguity neutrality (e.g., Li et al., 2018), while others argue that in certain situations of uncertainty, it may be rational to reject ambiguity neutrality (e.g., Gilboa et al., 2009).

The degree of deviations from perfect rationality would then depend on how well the Bayesian Entrepreneurship training allows the entrepreneur to form well calibrated probability assessments along the probability distribution. This is yet unclear from the experiments conducted in Bayesian Entrepreneurship. What has been discovered so far is that entrepreneurs taking the training make better decisions, which of course is comforting. But it is unclear if the theory of Bayesian Entrepreneurship affects only calibration accuracy and consistency, or how people combine judgments and preferences to reach a decision (i.e. their decision model, point 3 above), or both. Future work will need to become more precise and decide how to address this challenge. For example, if we for a moment presume that the entrepreneur prior to participating in the experiment was behaving as governed by RST, then obtaining stronger support for the correct hypothesis would both move the expectation closer to the population base rate, and make the calibration curve less flat. If, on the other hand, the entrepreneur prior to participating in the experiment was behaving as governed by CBR, then the key impact would be to move the entrepreneur away from the influence of experienced cases and towards the sampling mean from the experiment. Given different theoretical starting points, the training may show vastly different treatment effects. In other words, knowing which biases and heuristics affect poor decisions by entrepreneurs (to start with) helps to understand how training in Bayesian Entrepreneurship might or might not improve decision accuracy (point 4 above).

Training decision-makers to have better calibrated beliefs, have better judgment, and make better choices has been the focus of many studies (see e.g. Fischhoff and Broomell, 2020). Two alternative approaches to training emerge which address the subject of erroneous decisions differently: debiasing, and changing the decision rules (Larrick, 2004). Debiasing focuses on well-known human biases and designs training methods for a decision-maker to realize they have biased beliefs and to make corrections. The most general way to describe these efforts is to get the decision maker to switch from System-1 thinking to System-2 thinking, from unconscious and automatic choices to conscious and deliberate choices. This has met with some success (Larrick, 2004; Lawson et al., 2020). The second approach is to make the decision maker switch from relying on inferior strategies or decision rules to superior, more normative rules. An example of the former decision rules might be “take the first option that appears”, while the second strategy would be “collect more information, and take the best option among a set of options”. In our reading of Bayesian Entrepreneurship, it seems that it primarily touches on training the entrepreneur to learn superior decision rules (point 5 above), but this remains unclear, and it is unclear what those superior decision rules are; this should be clarified in the future.

To take an example of superior training and calibration, weather forecasters have historically been extremely good at probabilistic forecasting, where ex-ante probability forecasts land almost perfectly on the ex-post objective probabilities (see e.g. Murphy & Winkler, 1977). The reader should compare Figures 2 and 3 to get a sense of the mile-wide difference between weather forecasters’ and (highly experienced) entrepreneurial venture judges' calibration accuracy!

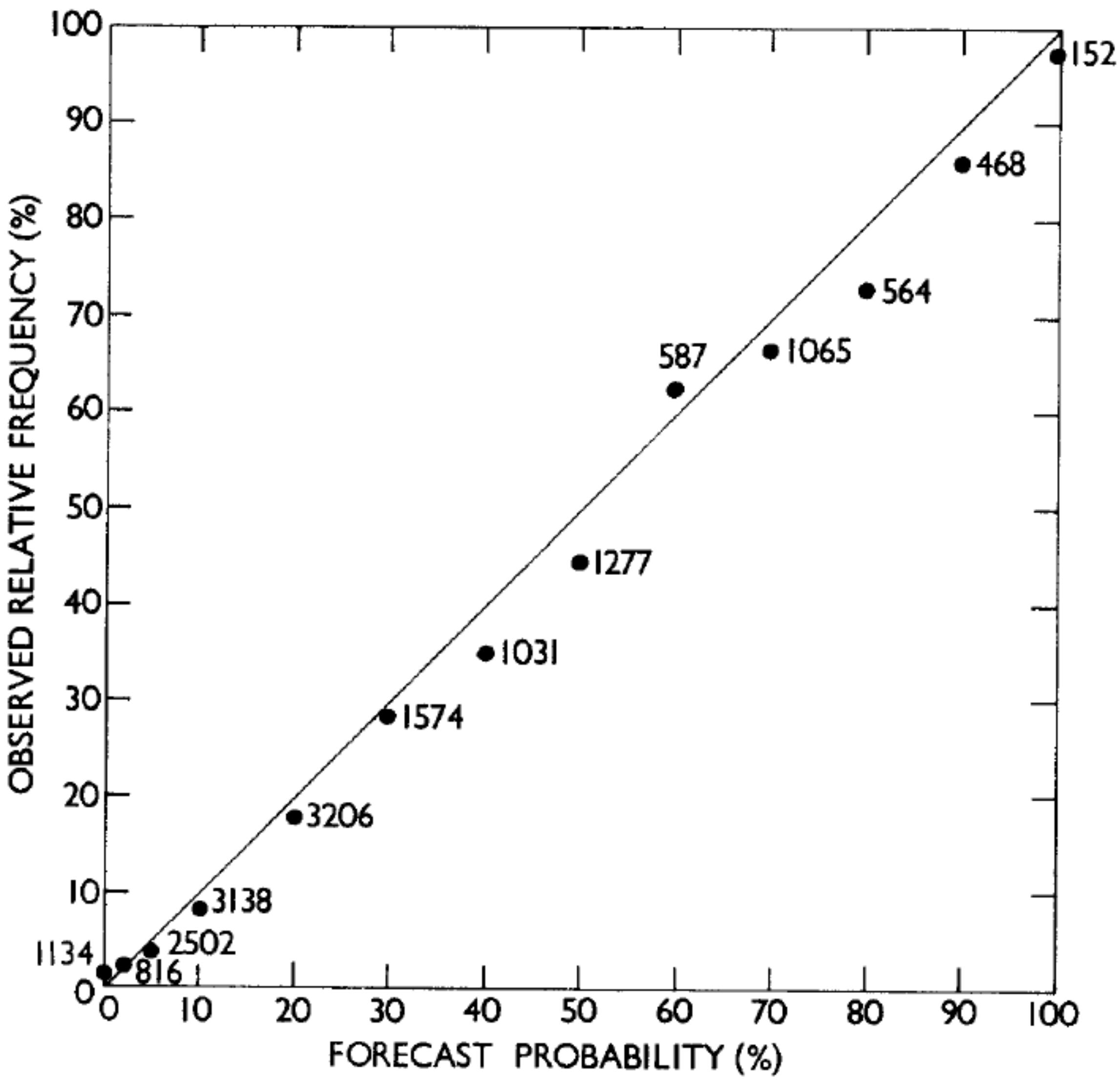


**Figure 3. Calibration curve for U.S. weather forecasters.** *Notes*: The numbers in the Figure represent the number of forecasts. Weather forecasters show some overprediction of most probabilities, except for very low and high probability events. Forecasters could choose among 2, 5, 10, 20, …, 90 and 100 % probability of the event "precipitation".

Three reasons for these differences are the deliberate decision process, the reliance on technical decision support, and the readily available feedback for weather forecasters. Entrepreneurship scholars may consider weather forecasting and entrepreneurship to be two completely different things that cannot be compared. However, for those that doubt that probabilistic estimation is possible even under extreme uncertainty, one need not look further than the many articles produced by “the good judgment project”. In this project, forecasters were asked to make predictions on questions such as “Will any country officially announce its intention to withdraw from the Eurozone before April 1, 2013?“ Forecasters expressed their beliefs by answering the question, “How likely is this event?” Probability judgments were later validated against actual outcomes.

A number of results came out from this project, most of which are summarized in Atanasov et al. (2017) and Moore et al. (2017). Some individuals turn out to be consistently better than others at predicting highly uncertain events; probabilistic training, incentives, and calibrated aggregation models improve predictions; and both competition and teamwork help in making better forecasts. Training appeared to reduce overconfidence even many months after the training completed. This is partially an effect of obtaining feedback on the accuracy of their forecasts. The project illustrates that with tools driving individuals to invoke System-2 thinking, training improves both the ability of judging future events and individuals’ confidence in making their forecasts.

We round off the description of the various theories for entrepreneurial decision making by reverting back to Figure 1, updating it with the relative position of Bayesian Entrepreneurship to form Figure 4. We have traversed from the normative theory of EUT, which states how a decision maker should use information to choose the most favorable option in the expectation, to theories that take into account that probabilities may not be commonly known but can be subjectively perceived, to models where part of the probabilities as well as choices and outcomes are unavailable as they depend on a limited set of imagined or recalled cases, and finally to verbal models of decision making where there is even more uncertainty, characterized for example by a lack of knowledge about the relations between causes and effects.

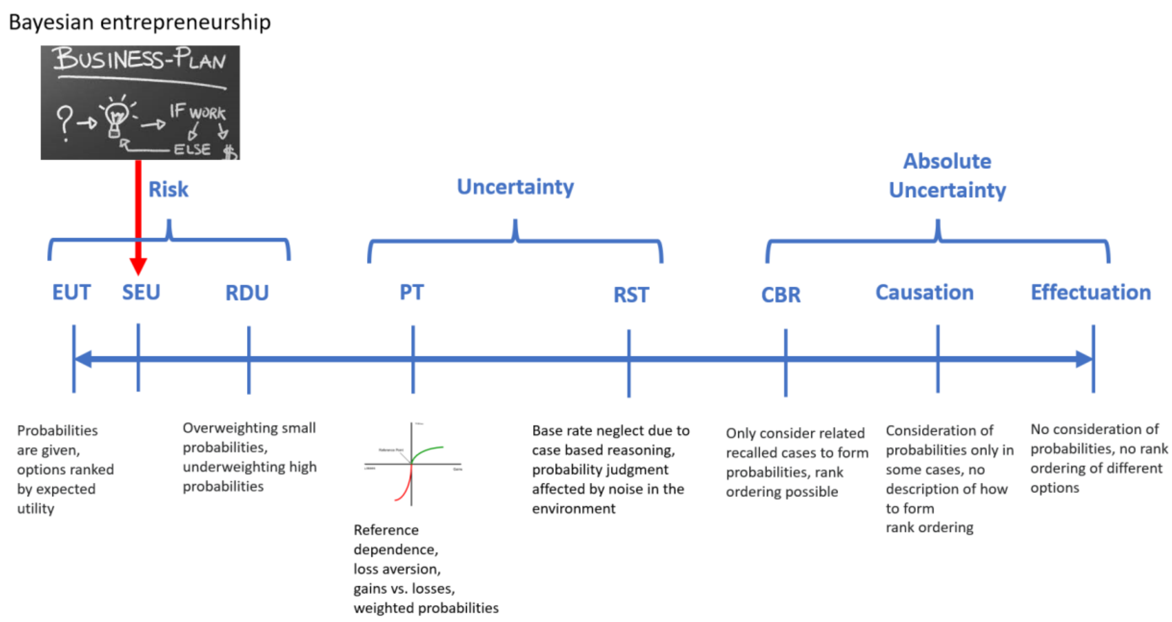


**Figure 4. Bayesian entrepreneurship's position among theories of entrepreneurial judgment under risk, uncertainty, and absolute uncertainty.** *Notes*: Picture credits to Daniel Chen and Jonathan Houston. EUT: Expected Utility Theory; RDU: Rank Dependent Utility; PT: Prospect Theory; RST: Random Support Theory; CBR: Case-Based Reasoning.

# Conclusion

This Chapter concludes that there is still a void between economists and decision theorists on the one hand, and entrepreneurship scholars on the other, in terms of characterizing judgment and decision-making under uncertainty. Decision theorists have made considerable strides in moving away from expected utility theory to more "realistic" models, thus meeting entrepreneurship scholars' understanding of the decision environment. They have for example analyzed the effects of incomplete information, unclear causal effects, and a general degree of ambiguity of the decision space. But, as opposed to the theories of entrepreneurship scholars, this ambiguity is still parametrized. The work of decision theorists has led to new insights, for example explaining satisficing behavior and aspiration levels using a specific modeling framework. Maybe the most fundamental understanding emanating from this review that impacts the theory of Bayesian Formation is that entrepreneurs may come to strikingly different valuations of an opportunity by for example having different probability weighting functions, or by having different recalled cases to form an estimate from, to have different evaluation models, or by being biased in various ways. Entrepreneurs may, but certainly need not be more optimistic than other people to perceive an opportunity differently. This calls for theorizing on Bayesian Entrepreneurship to clarify the first stage of the theory – the process of forming a "contrarian" belief – even further.[9]

A recent literature has started a more pragmatic approach trying to help entrepreneurs reduce uncertainty so that they can move as much as possible to a more scientific and rational approach to making decisions. This literature has been supported by a plethora of practical tools aimed at helping entrepreneurs make better decisions. Some of these may work better than others. Bayesian Entrepreneurship theory is proposing one practical tool which involves formulating a hypothesis and conducting an experiment to test it. It is unclear how this nascent theory maps into received theories of decision making. We have made an attempt at initiating this mapping. It remains unclear to us how the theory maps into the standard view of decision making in terms of affecting beliefs, heuristics, or both, and how it explains the improvements in entrepreneurial behavior that have been demonstrated in experiments. We do not dispute the experimental results, but rather seek clarification of how the theory operates both on beliefs and heuristics. Understanding this would allow the design of more precise experiments and allow for testing the proposed mechanisms of human behavior. As it is a theory that involves training of entrepreneurs,

[9] See e.g. Felin et al. (2024) for an initial attempt.

it also seems useful to clarify how it maps to other training methods that either try to debias beliefs or change poor decision rules. We have indicated where to start this clarification as well.

# References

Abdellaoui, M., Baillon, A., Placido, L., & Wakker, P. P. (2011). The rich domain of uncertainty: Source functions and their experimental implementation. *American Economic Review*, 101(2), 695-723.

Agrawal, A., Camuffo, A., Gambardella, A., Gans, J. S., Scott, E. L., & Stern, S. (this volume). Bayesian entrepreneurship. MIT Press.

Ahn, T. (2010). Attitudes toward risk and self-employment of young workers. *Labour Economics*, 17(2), 434-442.

Atanasov, P., Rescober, P., Stone, E., Swift, S.A., Servan-Schreiber, E., et al. (2017). Distilling the wisdom of crowds: prediction markets versus prediction polls. *Management Science* 63(3), 691-706.

Allais, M. (1953). Le comportement de l'homme rationnel devant le risque: critique des postulats et axiomes de l'école américaine. *Econometrica: Journal of the Econometric Society*, 503-546.

Åstebro T., & Elhedhli, S. (2006). The effectiveness of simple decision heuristics: forecasting commercial success for early-stage ventures, *Management Science*, 52(3), 395–409.

Åstebro, T., Herz, H., Nanda, R., & Weber, R. A. (2014). Seeking the roots of entrepreneurship: Insights from behavioral economics. *Journal of Economic Perspectives*, *28*(3), 49-70.

Åstebro T., & Koehler, D. (2007). Calibration accuracy of a judgmental process that predicts the commercial success of new product ideas. *Journal of Behavioral Decision Making*, 20(4), 381-403.

Barberis, N. C. (2013). Thirty years of prospect theory in economics: A review and assessment. *Journal of Economic Perspectives*, 27(1), 173-196.

Brenner, L. A. (1995). A stochastic model of the calibration of subjective probabilities. Stanford University.

Brenner, L. A. (2003). A random support model of the calibration of subjective probabilities. *Organizational Behavior and Human Decision Processes*, 90(1), 87-110.

Brenner, L., Griffin, D., & Koehler, D. J. (2006). Modeling patterns of probability calibration with random support theory: Diagnosing case-based judgment. *Organizational Behavior and Human Decision Processes*, 97, 64–81.

Brockhaus Sr, R. H. (1980). Risk taking propensity of entrepreneurs. *Academy of Management Journal*, *23*(3), 509-520.

Busenitz, L. W., & Barney, J. B. (1997). Differences between entrepreneurs and managers in large organizations: Biases and heuristics in strategic decision-making. *Journal of Business Venturing*, *12*(1), 9-30.

Camuffo, A., Cordova, A., Gambardella, A., & Spina, C. (2020). A scientific approach to entrepreneurial decision making: Evidence from a randomized control trial. *Management Science*, *66*(2), 564-586.

Camuffo, A., Gambardella, A., Messinese, D., Novelli, E., Paolucci, E., & Spina, C. (2024). A scientific approach to entrepreneurial decision-making: Large-scale replication and extension. *Strategic Management Journ*al, 45(6), 1209-1237.

Camuffo, A., Gambardella, A., & Pignataro, A. (2023). Theory-driven strategic management decisions. CEPR DP 17664v2.

Coali, A., Gambardella, A., & Novelli, E. (2024). Scientific decision-making, project selection and longer-term outcomes. *Research Policy*, *53*(6), 105022.

Cooper, A. C., Woo, C. Y., & Dunkelberg, W. C. (1988). Entrepreneurs' perceived chances for success. *Journal of Business Venturing*, 3(2), 97-108.

Caliendo, M., Fossen, F. M., & Kritikos, A. S. (2009). Risk attitudes of nascent entrepreneurs–new evidence from an experimentally validated survey. *Small Business Economics*, 32, 153-167.

Cramer, J. S., Hartog, J., Jonker, N., & Van Praag, C. M. (2002). Low risk aversion encourages the choice for entrepreneurship: an empirical test of a truism. *Journal of Economic Behavior & Organization*, 48(1), 29-36.

Cyert, R., & March, J. (2015). Behavioral theory of the firm. In *Organizational Behavior 2* (pp. 60-77). Routledge.

De Meza, D., Dawson, C., Henley, A., & Arabsheibani, G. R. (2019). Curb your enthusiasm: Optimistic entrepreneurs earn less. *European Economic Review*, *111*, 53-69.

Dell'Era, M., Opromolla, L. D., & Santos-Pinto, L. (2023). Can optimism solve the entrepreneurial earnings puzzle?. *The Scandinavian Journal of Economics*, *125*(1), 139-169.

Diecidue, E., & Wakker, P. P. (2001). On the intuition of rank-dependent utility. *Journal of Risk and Uncertainty*, 23, 281-298.

Ellsberg, D. (1961). Risk, ambiguity, and the Savage axioms. *The Quarterly Journal of Economics*, 75(4), 643-669.

Felin, T., Gambardella, A., Novelli, E., & Zenger, T. (2024). A scientific method for startups. *Journal of Management*, forthcoming. https://doi.org/10.1177/01492063231226136

Fischhoff, B., & Broomell, S. B. (2020). Judgment and decision making. *Annual Review of Psychology*, *71*(1), 331-355.

Foss, N. J., & Klein, P. G. (2012). Organizing entrepreneurial judgment. Cambridge, UK: Cambridge University Press.

Foss, N. J., & Klein, P. G. (2020). Entrepreneurial opportunities: Who needs them?. *Academy of Management Perspectives*, 34(3), 366-377.

Fox, C. R., Erner, C., & Walters, D. J. (2015). Decision under risk: From the field to the laboratory and back. The Wiley Blackwell Handbook of Judgment and Decision Making, 2, 41-88.

Fox, C. R., & Tversky, A. (1998). A belief-based account of decision under uncertainty. *Management Science*, 44(7), 879-895.

Frenkel-Brunswick, E. (1951). Personality theory and perception. In R. Blake, & E. Ramsey (Eds.), *Perception: An Approach to Personality*. New York: Ronald.

Furnham, A., & Marks, J. (2013). Tolerance of ambiguity: A review of the recent literature. *Psychology*, *4*(09), 717-728.

Gilboa, I. (1987). Expected utility with purely subjective non-additive probabilities. *Journal of Mathematical Economics*, 16(1), 65-88.

Gilboa, I., & Schmeidler, D. (1989). Maxmin expected utility with non-unique prior. *Journal of Mathematical Economics*, 18(2), 141-153.

Gilboa, I., Postlewaite, A., & Schmeidler, D. (2009). Is it always rational to satisfy Savage's axioms? *Economics & Philosophy*, 25(3), 285-296.

Gilboa, I., Schmeidler, D. (1995) Case-based decision theory, *The Quarterly Journal of Economics*, 110(3), 605–639.

Gutierrez, C., Åstebro, T., & Obloj, T. (2020). The impact of overconfidence and ambiguity attitude on market entry. *Organization Science*, 31(2), 308-329.

Holm, H. J., Opper, S., & Nee, V. (2013). Entrepreneurs under uncertainty: An economic experiment in China. *Management Science*, 59(7), 1671-1687.

Johnson, B. R. (1990). Toward a multidimensional model of entrepreneurship: The case of achievement motivation and the entrepreneur. *Entrepreneurship Theory and Practice*, *14*(3), 39-54.

Kahneman, D., & Tversky, A. (1973). On the psychology of prediction. *Psychological Review*, 80(4), 237.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decisions under risk. *Econometrica*, 47(2), 263-292.

Kihlstrom, R. E., & Laffont, J. J. (1979). A general equilibrium entrepreneurial theory of firm formation based on risk aversion. *Journal of Political Economy*, 87(4), 719-748.

Knight, F. H. (1921). *Risk, uncertainty and profit* (Vol. 31). Houghton Mifflin.

Koehler, D. J., Brenner, L., & Griffin, D. (2002). The calibration of expert judgment: Heuristics and biases beyond the laboratory. In Gilovich, T., Griffin, D., & Kahneman, D. (Eds.), Heuristics and biases: The psychology of intuitive judgment (pp. 686–715). Cambridge University Press.

Koudstaal, M., Sloof, R., & Van Praag, M. (2016). Risk, uncertainty, and entrepreneurship: Evidence from a lab-in-the-field experiment. *Management Science*, 62(10), 2897-2915.

Laferrière, V., Staubli, D., & Thöni, C. (2023). Explaining excess entry in winner-take-all markets. *Management Science*, 69(2), 1050-1069.

Larrick, R. P. (2004). Debiasing. In D. J. Koehler & N. Harvey (Eds.), Blackwell Handbook of Judgment and Decision Making (pp. 316-337). Oxford: UK

Lawson, M. A., Larrick, R. P., & Soll, J. B. (2020). Comparing fast thinking and slow thinking: The relative benefits of interventions, individual differences, and inferential rules. *Judgment and Decision Making*, 15(5), 660-684.

Li, Z., Müller, J., Wakker, P. P., & Wang, T. V. (2018). The rich domain of ambiguity explored. *Management Science*, 64(7), 3227-3240.

McMullen, J. S., & Shepherd, D. A. (2006). Entrepreneurial action and the role of uncertainty in the theory of the entrepreneur. *Academy of Management Review*, *31*(1), 132-152.

Moore, D. A., & Cain, D. M. (2007). Overconfidence and underconfidence: When and why people underestimate (and overestimate) the competition. *Organizational Behavior and Human Decision Processes*, *103*(2), 197-213.

Moore, D. A., & Healy, P. J. (2008). The trouble with overconfidence. *Psychological Review*, 115 (2), 502-517.

Moore, D. A.,, Swift, S. A., Minster, A., Mellers, B. A., Ungar, L. H., et al. (2017). Confidence calibration in a multiyear geopolitical forecasting competition. *Management Science* 63(11), 3552-65.

Murphy, A. H., & Winkler, R. L. (1977). Reliability of subjective probability forecasts of precipitation and temperature. *Journal of the Royal Statistical Society. Series C (Applied Statistics)*, 26(1), 41-47.

Nishimura, K. G., & Ozaki, H. (2004). Search and Knightian uncertainty. *Journal of Economic Theory*, *119*(2), 299-333.

Packard, M. D., Clark, B. B., & Klein, P. G. (2017). Uncertainty types and transitions in the entrepreneurial process. *Organization Science*, *28*(5), 840-856.

Quiggin, J. (1982). A theory of anticipated utility. *Journal of Economic Behavior & Organization*, 3(4), 323-343.

Sarasvathy, S. D. (2001). Causation and effectuation: Toward a theoretical shift from economic inevitability to entrepreneurial contingency. *Academy of Management Review*, 26(2), 243-263.

Savage, L. J. (1951). The theory of statistical decision. *Journal of the American Statistical Association*, 46(253), 55-67.

Savage, L. J. (1954). *The foundations of statistics*. Reprint Dover (1974). New York.

Schmeidler, D. (1989). Subjective probability and expected utility without additivity. *Econometrica*, 57(3), 571-587.

Sexton, D. L., & Bowman, N. (1985). The entrepreneur: A capable executive and more. *Journal of Business Venturing*, *1*(1), 129-140.

Shane, S. (2009). Why encouraging more people to become entrepreneurs is bad public policy. *Small Business Economics*, 33, 141-149.

Shepherd, D. A., McMullen, J. S., & Jennings, P. D. (2007). The formation of opportunity beliefs: Overcoming ignorance and reducing doubt. *Strategic Entrepreneurship Journal*, *1*(1-2), 75-95.

Simon, H. A. (2013). *Administrative Behavior*. Simon and Schuster.

Skriabikova, O. J., Dohmen, T., & Kriechel, B. (2014). New evidence on the relationship between risk attitudes and self-employment. *Labour Economics*, 30, 176-184.

Starmer, C. (2000). Developments in non-expected utility theory: The hunt for a descriptive theory of choice under risk. *Journal of Economic Literature*, 38(2), 332-382.

Stewart, W. H., & Roth, P. L. (2007). A meta-analysis of achievement motivation differences between entrepreneurs and managers. *Journal of Small Business Management*, *45*(4), 401-421.

Townsend, D. M., Hunt, R. A., McMullen, J. S., & Sarasvathy, S. D. (2018). Uncertainty, knowledge problems, and entrepreneurial action. *Academy of Management Annals*, *12*(2), 659-687.

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases: Biases in judgments reveal some heuristics of thinking under uncertainty. *Science*, 185(4157), 1124-1131.

Tversky, A., & Kahneman, D. (1983). Extensional versus intuitive reasoning: The conjunction fallacy in probability judgment. *Psychological Review*, 90(4), 293.

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, 5, 297-323.

Von Neumann, J., & Morgenstern, O. (1953). *Theory of games and economic behavior* (third ed.). Princeton, NJ: Princeton University Press.

Wu, B., & Knott, A. M. (2006). Entrepreneurial risk and market entry. *Management Science*, 52(9), 1315-1330.

Zellweger, T., & Zenger, T. (2023). Entrepreneurs as scientists: A pragmatist approach to producing value out of uncertainty. *Academy of Management Review*, 48(3), 379-408.