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Theory-Based Entrepreneurial Search

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Abstract. How should Theory-based entrepreneurs search for strategies to implement their ideas? The theory-based view of strategy posits that decision makers hold key conjectures about their path to success and use theory to understand and test beliefs underlying those conjectures. This causal framework also has implications for entrepreneurial search: the process by which entrepreneurs uncover strategies to implement their ideas. In this paper, we develop a Bayesian model where entrepreneurs update their beliefs as they conduct entrepreneurial search. We find several optimal behaviors for Theory-based entrepreneurs such as reverting to a previous strategy after finding a relatively poor strategy and continuing to search after finding a relatively good strategy, which are missing when entrepreneurs lack such a theory-based approach. As our theoretical predictions align with examples of successful entrepreneurs, our findings both provide a method to empirically identify Theory-based entrepreneurs and demonstrate the usefulness of applying the theory-based view to entrepreneurial behavior more generally.

Keywords: entrepreneurial search • theory-based view • stopping rule • Bayesian learning • Knightian uncertainty • entrepreneurial strategy • experimentation

1. Introduction

The theory-based view of strategy postulates that gathering data about the environment leads not only to learning about the environment but also the re-evaluation of causally linked assumptions and conjectures about that environment: learning alters one's theory of how the world works (Felin and Zenger 2009, 2017; Ehrig and Schmidt 2022). Although the theory-based view applies to a broad range of strategic decision-making contexts, it is especially relevant to the choices made by entrepreneurs (Gans et al. 2019, 2024). Entrepreneurs often develop new markets, invent new technologies, or apply new organizational forms (Botelho et al. 2021), and therefore must make decisions in situations where limited prior knowledge is available (Kirzner 1997). While entrepreneurs can employ simple trial-and-error in their decision making (Sarasvathy 2001, Bhide 2003), the theory-based view provides a more proactive approach whereby entrepreneurs interpret their early experiments to alter their beliefs and future decision making (Murray and Tripsas 2004, Felin and Zenger 2009, Gans et al. 2019). The entrepreneur's goal is not just to discover a good action but also to uncover information that they interpret through theory to update their beliefs. Based on these updated beliefs, their revised conjectures then improve decision making about which future steps to take (Felin et al. 2024).

How might the "theory" that an entrepreneur holds shape the choices made regarding a given entrepreneurial opportunity? Consider the contrasting theories maintained by the McDonald brothers, who founded McDonald's, and Ray Kroc, who sought to purchase the McDonald's name and system in order to turn it into a worldwide phenomenon (Kroc and Anderson 1987). Both sets of entrepreneurs were aware of the same idea (the "Speedee" fast food system that the McDonald brothers invented) and agreed on the evidence from the first experiment (the out-sized success of the early McDonald's restaurants). Notably, Kroc became first aware of the McDonald's restaurants because they needed eight milkshake machines to meet demand, whereas a typical restaurant of the time needed just one. While the McDonald brothers viewed their success as a once-in-a-generation restaurant triumph, Ray Kroc instead believed the success demonstrated the potential for even greater success in the future. At least in part, Kroc's belief was based on the understanding that the performance of the first McDonald's stores was "extreme" relative to other restaurants, falsifying the basic premise that McDonald's was simply a successful restaurant. Ray Kroc effectively employed a causal logic model in which McDonald's was a new kind of business, that is, fast food, with much larger potential than a traditional restaurant. Hence, the theory that Ray Kroc held, as opposed to the more pragmatic approach of the McDonald's brothers, led him to make choices that allowed him to translate the nascent idea reflected in the first McDonald's stores into a global franchise.

The purpose of this paper is to identify the distinctive ways that the theory-based view informs entrepreneurial search behavior and choice. Specifically, we present a Bayesian model of entrepreneurial search, where entrepreneurs are not only uncertain about the value of the specific strategies but also uncertain about the distribution of value from which strategies are drawn (as in Gans et al. (2019) and sometimes referred to as "second-order probabilities", e.g., Camerer and Weber (1992)). Different theories are associated with different probability distributions so testing a strategy not only allows the entrepreneur to assess the value of that strategy but also allows entrepreneurs to update their beliefs about the nature of the distribution on which search is being conducted and the validity of each theory. We contrast the behaviors of two types of entrepreneurs: a *Theory-based entrepreneur*, who reevaluates their underlying theory by inferring which distribution draws are taken from, and a *Practice-based entrepreneur*, who, while correctly assessing the value of a tested strategy, does not consider its higher-order implications for their overall theory of value creation and capture. In other words, this paper contrasts the search behavior of a "sophisticated" Theory-based entrepreneur who is actively interrogating the causal structure underlying their environment versus a more "pragmatic" Practice-based entrepreneur who does not.

Our results show that whether an entrepreneur is theory-based or practice-based has a profound impact on entrepreneurial search and choice. First, Theory-based entrepreneurs can be more tenacious searchers. Whereas a Practice-based entrepreneur might be satisfied after discovering a sufficiently valuable strategy and choose to lock in their gains by committing to that strategy, a Theory-based entrepreneur might infer they are "drawing from a good distribution" and so continue searching in order to uncover an even more promising strategy. Second, "pivots" by Theory-based entrepreneurs are qualitatively different from those by Practice-based entrepreneurs. Practice-based entrepreneurs will always pursue new strategies when they uncover that an existing strategy fails their expectations and will never revise their beliefs after such disappointments. In contrast, a Theory-based entrepreneur would be willing to revert to a prior strategy despite having previously dismissed its payoff as being unsatisfactory. Third, we also show that only Theory-based entrepreneurs value experts who hold an informational advantage that allows the identification of the distribution from which strategies are drawn. This suggests that heterogeneity in preferences for experts such as venture capitalists, mentors, or industry veterans among entrepreneurs may, at least in part, stem from the "mindset" of the entrepreneur. Theory-based entrepreneurs are more likely to value venture capitalists or mentors with prior experience in their idea's context as such experts can assist entrepreneurs to learn about the environment while searching for strategies.

Our analysis suggests that entrepreneurs facing a high degree of uncertainty may benefit from a more theory-based approach to entrepreneurial search. Startups exploring ideas with at least some potential for out-sized growth (e.g., those exploring a new technology, a new market, or a new organizational form) face uncertainty that is of a more fundamental nature than simply whether a particular strategy "works". There is a higher likelihood that their premises (and thereby theory) may be incorrect, and therefore would benefit from re-evaluating those premises based on the information gained during search (Gans et al. 2018, Agrawal et al. 2021, Gans 2023). As such, our results also offer distinct empirical implications. While one cannot directly observe the mindset of an entrepreneur as they conduct search and make choices, the specific predictions associated with the theory-based view allow us to classify entrepreneurs according to their decision-making patterns. For example, entrepreneurs who continue to search after they identify one strategy that works, but who also are ultimately able to discontinue search and revert to a previous strategy as they gain an understanding of their environment, are undertaking behaviors consistent with the theory-based approach and inconsistent with the practice-based approach. In high-growth contexts, behaviors consistent with the theory-based approach could also be a proxy to identify a certain kind of entrepreneurial "skill". Therefore, studying the relationship between venture outcomes and entrepreneurial search behavior is a promising direction for future empirical work. Finally, under theory-based entrepreneurship, an additional mechanism exists by which venture capitalists (Kaplan and Strömberg 2001, Bernstein et al. 2016) and other types of advisors (Åstebro and Gerchak 2001, Assenova 2020, Hallen et al. 2020) may provide a distinct type of value to entrepreneurs and so suggests an additional channel by which such entities can affect entrepreneurial outcomes (Hsu 2004).

The rest of this paper proceeds as follows. Section 2 describes how Theory-based entrepreneurs differ from Practice-based ones. Section 3 then uses a specific distributional example to outline our main results. Section 4 provides a general statement of our results by building a formal model. Section 5 explores how differences in how each type of entrepreneur values the same idea lead to differences in behaviors. A final section concludes.

2. Theory-Based vs. Practice-Based Entrepreneurs

2.1. Distinguishing the Type of Entrepreneur

How does the search for strategies differ between an entrepreneur taking a theory-based approach and an entrepreneur who does not? Consider first a Practice-based entrepreneur. Given an entrepreneurial idea, this entrepreneur will seek to exploit their idea through experimentation and learning (see Felin et al. 2024), subject to constraints such as prototyping costs or delayed time to market. While this Practice-based entrepreneur acknowledges there is uncertainty about how well each possible strategy may play out, their evaluation of the underlying idea remains fixed because they lack a theory about how the idea creates and captures value. In other words, there is no causal chain identifying beliefs that can be tested through experimentation. In effect, while a Practice-based entrepreneur learns about specific strategies during the search process, they do not learn about their environment and thereby the distinct value of their idea. Instead, the Practice-based entrepreneur focuses on the rapid testing of individual strategies (Blank 2013).

In contrast, a Theory-based entrepreneur holds a more abstract understanding of their environment, having several potential theories that could explain observed phenomena, each with different implications for the value of their idea. Experimentation involves not only learning about the specific strategy tested but also shifting their confidence in each of their theories and consequently how they value their idea (Camuffo et al. 2020, Ehrig and Schmidt 2022, Rindova and Martins 2024). When they experiment on a particular strategy, they learn not only about the strategy but also about the likelihood each of their theories is correct. They can compare the experimental payoff of their tested strategy against the range of possibilities generated by their main working theory as well as against those generated by their alternative theories. Given a discrepancy between the strategy's outcome and what their working theory would predict, they might question the premises behind their working theory and increase their confidence in an alternative. If the discrepancy is large enough, their working theory might switch to one of their alternative theories. In other words, the learning generated by search can by itself lead to changing beliefs about which theory is most likely true (Felin and Zenger 2009).

We can illustrate this process by describing a hypothetical entrepreneur with the idea of selling software to manufacturing firms. A Theory-based entrepreneur has a causal logic underlying their priors on the caliber of their idea by which they judge the success of their strategies. Following Ehrig and Schmidt (2022), they have a set of beliefs about their environment, for example, that their software moderately reduces manufacturing costs for their customers, and that if their product moderately reduces manufacturing costs, some customers will buy it. The derived belief that customers will buy their product is a conjecture that follows from the original set of beliefs. Their working theory provides causal logic through which they interpret their observations: if customers are buying their product, that is, their conjecture holds, it is because it moderately reduces manufacturing costs. Importantly, this theory also implies a certain probability distribution of outcomes. Because the customer benefit is moderate, it is more likely that any discovered strategy to execute their idea will result in moderate rather than wild success for their startup.

But because the entrepreneur is theory-based, they also acknowledge there could be other causal logics, that is, alternative theories, that could explain the derived conjecture. It is possible that their software not only reduces costs but also significantly improves the quality of any manufactured goods. While this alternate theory based on this belief would yield the same prediction that customers will buy the product, the reason would be different. Importantly, this alternative causal logic implies a different distribution of potential outcomes. Under the alternative theory, it is possible to uncover a strategy that yields an exceptional outcome, as a significant improvement in quality would be well-appreciated by a manufacturer's end customers. Now consider an experiment where the entrepreneur offers a "minimal" version of the product at an industry trade show. Suppose the experiment yields higher-than-expected sales and fawning product reviews by these early customers. Then the Theory-based entrepreneur might infer that their alternative theory is more likely to be true than their working theory and adjust their beliefs in favor of their alternative theory. This change in beliefs has distinct implications for strategy: it for example might now be worthwhile to raise considerable external funds to hire a first-class sales force or build a more fully featured version of the product itself. Hence, for a Theory-based entrepreneur, experimenting is not just about testing a particular strategy, but learning about the potential of other possible strategies.

It's not uncommon for different theories to lead to the same conjuncture but imply a different distribution of outcomes for entrepreneurial firms, especially in new industries. For a real-world example, consider online grocery delivery in the early days of the Internet. At the time, the two entrepreneurial teams at Webvan and Peapod both shared the same conjecture that customers in the United States would shop online for their groceries. However, Webvan's working theory leading to this conjecture was premised on the assumption that online grocery would supplant traditional groceries (Glasner 2001), while Peapod's working theory was premised on online grocery becoming a value-added service for traditional grocers (Ahold Delhaize 2014). Both of these theories implied there were opportunities for entrepreneurial entry, but they had wildly different implications for outcomes. Under Webvan's theory, the potential was enormous, including the possibility for a single firm to completely replace an industry with hundreds of billions of dollars in annual sales.[1] Under Peapod's theory, online groceries would constitute a fraction of offline sales with brand loyalty staying with traditional groceries, limiting the potential outcomes. Hence two theories with the same conjecture implied different distributions of what would be possible to achieve, regardless of the specific strategy selected for execution.

2.2. Relation to Prior Work

Our approach to characterizing and then contrasting theory-based versus practice-based entrepreneurial behaviors builds on three distinct but related approaches to conceptualizing entrepreneurial decision making. First, a set of papers places malleable theory at the center of strategic decision making (Hsieh et al. 2007; Felin and Zenger 2009, 2017). This prior work takes the view that the Knightian style uncertainty faced by entrepreneurs (Knight 1921) makes finding optimal decisions across the landscape of potential options intractable without some theory to guide decision making. The first stage of entrepreneurship is effectively described as a cycle of theory refinement, where the causal structure of a theory helps entrepreneurs identify which theoretical beliefs need further testing and how to proceed given both positive and negative evaluations of those beliefs (Ehrig and Schmidt 2022, Wuebker et al. 2023). In our paper, we draw on this idea of theory-driven decision making but relax the literature's assumption that entrepreneurial learning primarily occurs in an experimentation phase where entrepreneurs are focused on testing the validity of their theory (Felin and Zenger 2009, Wuebker et al. 2023). Instead, we allow for entrepreneurial activity to be less structured, as suggested by recent empirical studies (Arikan et al. 2020, Rapp and Olbrich 2023) that find learning occurs across a wide variety of entrepreneurial activities, including entrepreneurial search as studied here.

Second, we rely on the formal literature on search, which evaluates optimal search behavior under distributional uncertainty (Chow and Robbins 1963, McCall 1965). A key insight of that literature is that, in contrast to a search with a known distribution where the search only stops above a predetermined "cut-off", uncertainty over the distribution results in a more complex stopping criterion, for example, leading to the possibility of stopping search after a sufficiently low draw (Rothschild 1974). Work building on Rothschild (1974) primarily focuses on identifying cases of distributional uncertainty where a cut-off rule could nonetheless be established (Weitzman 1978, Adam 2001). This search theory has been applied to several domains outside of entrepreneurship such as job search (Johnson 1978, Morgan 1983, Talmain 1992, Adam 2001), pricing (Rosenfield and Shapiro 1981), and strategic investments by established firms (Bernanke 1983, Tonks 1983, Jovanovic and Rob 1990, Keller et al. 2005). Our model also builds on Rothschild (1974) but instead explicitly focuses on cases when the cut-off rule fails to hold, in contrast to much of the prior work in this area.

Finally, there is a literature that focuses directly on how entrepreneurs discover and exploit new opportunities in an uncertain environment (Kirzner 1997, Shane and Venkataraman 2000). This uncertainty distinguishes the entrepreneurial case from the more general search for strategies literature (Levinthal 1997, Rivkin 2000), as entrepreneurs must both determine the properties of their environment while simultaneously identifying the most promising opportunities within that environment. Since the pursuit of a given opportunity by construction involves bringing together resources in a novel way to create and capture economic value, understanding how entrepreneurs assess novel opportunities (and the different ways of pursuing an opportunity) is a central element of entrepreneurship (Sarasvathy 2001, Smith and Cao 2007, Felin and Zenger 2009). A central insight in the study of opportunity identification and pursuit is that uncertainty impacts nearly every aspect of the discovery and exploitation of opportunities (Shane and Venkataraman 2000), including the identification of promising domains and specific opportunities (Ward 2004, Fiet et al. 2005, Baron and Ensley 2006, Fiet 2007, Fiet and Patel 2008, Gruber et al. 2008), the interplay between learning and entrepreneurial action (Gaglio and Katz 2001, Choi et al. 2008, Agrawal et al. 2021, Gans 2023, Rapp and Olbrich 2023), and the valuation of specific opportunities (Norton and Moore 2002, Chen et al. 2018, Camuffo et al. 2024).

Within this last literature, our focus in this paper is on how, given an uncertain idea or opportunity, entrepreneurs discover alternative ways to execute that idea, in other words, search for new strategies. We consider how entrepreneurs uncover such strategies (Alvarez and Barney 2007) as opposed to how they plan to execute an opportunity per se (Delmar and Shane 2003, Shane and Delmar 2004) or the importance of limiting search to domains of high expertise or potential learning (Fiet et al. 2005, Fiet 2007). Prior work on the search for strategies effectively focused on cases where the aforementioned cut-off rule results from assumptions about the type of uncertainty faced by an entrepreneur (Mosakowski 1997, Angus 2019). We argue that our knowledge of entrepreneurial search can be enhanced by exploring the implications of relaxing this assumption, as it predicts several behaviors observed in entrepreneurs that have thrived under significant environmental uncertainty, including shifting the "anchor" used as a baseline for search (Bhardwaj et al. 2006) and changing search behavior due to learning about the distribution of possible outcomes (Arentz et al. 2013, Goldstein et al. 2020).

We note that our approach effectively takes the mindset of the entrepreneur as exogenous: they do not choose to take one approach over the other. This is consistent with our desire to provide behavioral patterns that reveal the underlying skill of the entrepreneur as well as empirical work that suggests entrepreneurs often at least start with a practice-based mindset (Arentz et al. 2013, Goldstein et al. 2020). Camuffo et al. (2024) is in contrast an approach to general decision making, that is, broader than an entrepreneurial scope, that can be interpreted as merging the practice-based and theory-based mindsets. In their paper, a theory-based decision maker can opt to ignore alternative theories if the potential to gain information is too low or the cost of that information is too high. This effectively makes the decision-maker practice-based. We view their work as complementary to our own, as in many entrepreneurial settings, the potential to gain information from search, effectively one form of experimentation, is high (e.g. Bhardwaj et al. 2006). This paper effectively focuses on the case where their theory-based decision maker would opt to remain theory-based, while originally Practice-based entrepreneurs have no choice but to stay practice-based.

3. Basic Model

In this section, we will explain our results with an example using a specific functional form alongside anecdotes of analogous entrepreneurial behavior. First, we will describe the search problem from the perspective of each type of entrepreneur. Next, we will illustrate our main findings: Theory-based entrepreneurs may continue to search after relative success, revert to previous strategies, and value expert opinions. Section 4 contains the formal theorems of our main results that apply to a general set of probability distributions beyond the simple example used here with just two distributions.

Consider an entrepreneur who has an idea for a new venture. Following Gans et al. (2019), a large, inexhaustible set of possible strategies can be implemented to generate a payoff for the venture. The entrepreneur is resource-constrained and so can only implement one strategy. However, the entrepreneur can "test" any strategy in sequence, one at a time, before choosing which one to implement. After each test, the entrepreneur decides whether to continue searching for another strategy or stop at their previously best-found strategy.

The entrepreneur is risk-neutral and starts with an outside option with a payoff normalized to zero. The entrepreneur can choose to search for and test a strategy i by paying a positive cost c. For this example, we set $c = 0.15$. Doing so produces a signal x_i that is a positive real number that quantifies the expected return to the entrepreneur should the strategy i be implemented. Instead of searching, the entrepreneur can also choose to stop and execute the tested strategy with the highest expected return (or resort to their outside option if none of their found strategies had an expected return greater than zero).

There is a set of probability distributions $\mathcal{D}$, which govern the expected returns for strategies. For this example, we assume that there are two possible distributions (i.e., $|\mathcal{D}| = 2$) that represent two calibers of entrepreneurial ideas, varying by their potential outcomes. In one distribution, the idea is an "ordinary" idea and involves a distribution of returns which is normal with mean 1 and variance 1/2, i.e., $N(1, 1/2)$. For the other distribution, the idea is "exceptional" and involves a distribution with the same variance but a higher mean of 3, that is, $N(3, 1/2)$. If the entrepreneur is theory-based, they will be uncertain about the caliber of their idea: whether it is an ordinary idea or an exceptional one. We assign such a Theory-based entrepreneur with a prior probability of 0.75 on the idea being ordinary and of 0.25 on the being exceptional. In contrast, a Practice-based entrepreneur statically expects testing strategies to produce payoffs from a mixture distribution that is 75% $N(1, 1/2)$ and 25% $N(3, 1/2)$. Given the distributional assumptions used in our example, Figure 1 plots the distribution of strategies for each of these types of ideas (Panel A) as well as the mixture that results from their beliefs (Panel B).[2]

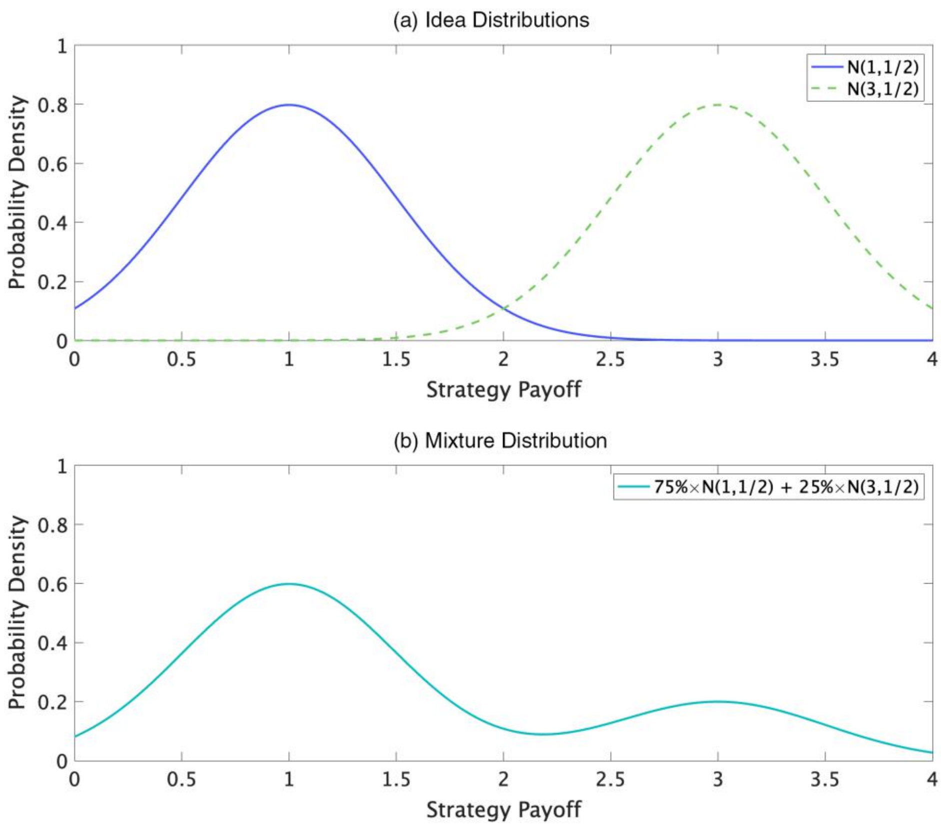
3.1. Don't Rest on Your Laurels

After testing a strategy, the entrepreneur needs to decide whether to continue by searching for and testing yet another strategy, or stop and execute the best strategy discovered so far. Proposition 2 in Section 4 states that Theory-based entrepreneurs may not "rest on their laurels", in the sense the discovery of a good strategy might lead them to search for even better ones, while a Practice-based entrepreneur might stop in the same situation.

Consider first the Practice-based entrepreneur who assumes that draws come from the fixed mixture distribution plotted in Figure 1(b). The optimal search behavior will be to stop searching as soon as a tested strategy is found with an expected outcome above a certain value (e.g., McCall (1965)). Above the cutoff, the probability of finding an even better strategy is too low to warrant continued search. Conversely, below the cutoff, the Practice-based entrepreneur will always continue searching. This cut-off value is a function of the mixture distribution and the cost c, which in our example is approximately 1.6.[3] Figure 2(a) depicts this stopping rule by showing the region where discovered strategy outcomes lead to continued search versus stopping for a Practice-based entrepreneur.

In contrast, the Theory-based entrepreneur has an optimal search strategy which may be nonmonotonic: the conditions for stopping versus continuing to search may switch at multiple points rather than at a single cut-off. This is because discovering a high-outcome

Figure 1. (Color online) Distributions of Strategy Outcomes

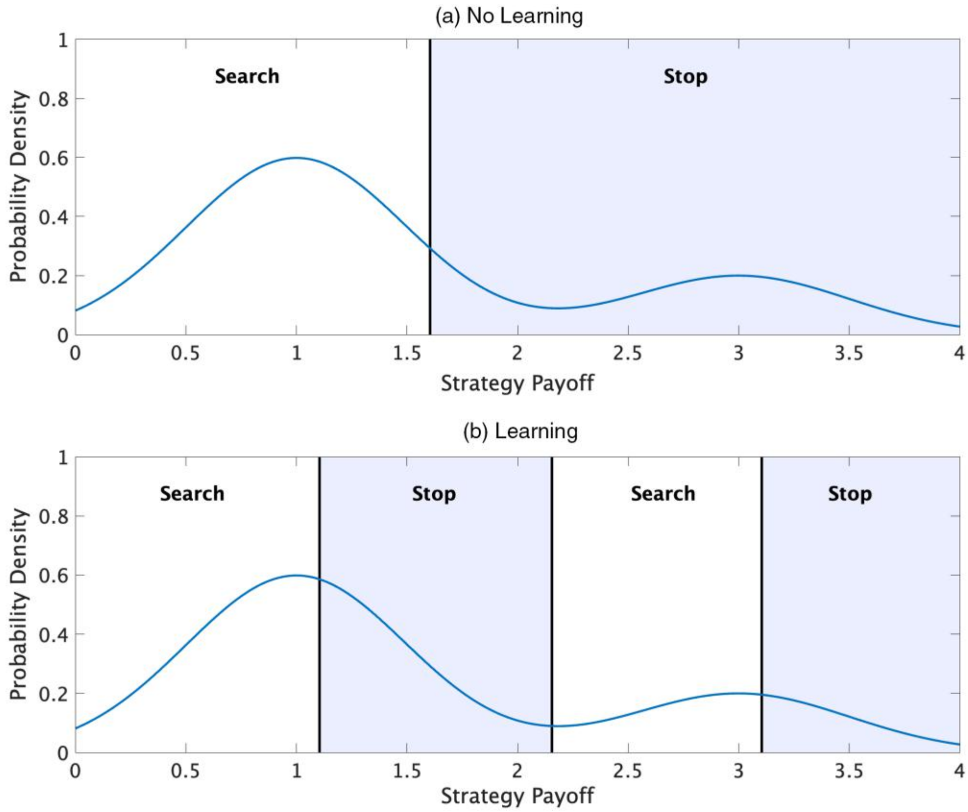


strategy can, counter-intuitively, lead to *more* search. When the entrepreneur believes they are on the ordinary distribution, discovering a high outcome strategy strengthens their alternative theory, making it more likely that they are searching the exceptional distribution. Thus, continuation can occur because it's possible to find yet a better strategy within the exceptional distribution. In our example as depicted in Figure 2(b), after discovering a strategy with an outcome less than about 1.1, search continues because even on the ordinary distribution, it's likely a better strategy can be uncovered.[4] Between 1.1 and about 2.2, stopping occurs because it is unlikely a better strategy can be drawn from the ordinary distribution. But above 2.2, the Theory-based entrepreneur becomes sufficiently convinced that their alternative theory is correct and their idea is drawing from the exceptional distribution. In the range between 2.2 and about 3.1, the entrepreneur believes they can find a better outcome from the exceptional distribution and continues to search. They stop if an outcome above 3.1 is found, as finding a better strategy is unlikely regardless of whether strategies are being drawn from the ordinary or exceptional distribution. Thus, there exists a range of higher-value outcomes where the Theory-based entrepreneur will continue searching while the Practice-based entrepreneur stops and implements the last strategy tested.

This theory-based behavior is perhaps best exemplified by the founding of Amazon. Prior to founding Amazon, Jeff Bezos was tasked with exploring the idea of using the Internet to reach customers, specifically for stock and bond trading, as he worked at D.E. Shaw, a Wall Street hedge fund (Stone 2013). These early explorations were successful as D.E. Shaw's stock trading site was an early online success story (Buckman and Gasparino 1999). However, Bezos viewed the potential of such early strategies leveraging the Internet as indicative that more was possible. While a Practice-based entrepreneur might have settled for the success of stock trading, Bezos continued searching for better strategies. Their decision to continue rather than stop search resulted in him leaving D.E. Shaw to start and launch the book-selling website Amazon (Bezos 1997).

Note that the difference in continuation behavior also implies that if there are relatively low-valued draws, the Theory-based entrepreneur chooses to implement those strategies rather than continue the search. In contrast, a Practice-based entrepreneur may continue searching. In Figure 2(b), this range lies between 1.1 and 1.6. Within this range, the Theory-based entrepreneur revises downward the likelihood that the distribution is exceptional, resulting in stopping, while the Practice-based entrepreneur would continue to search. Thus, a Theory-based entrepreneur not only refrains from resting on

Figure 2. (Color online) Optimal Stopping Decision



their laurels after discovering a good strategy but may relent after discovering a mediocre strategy.

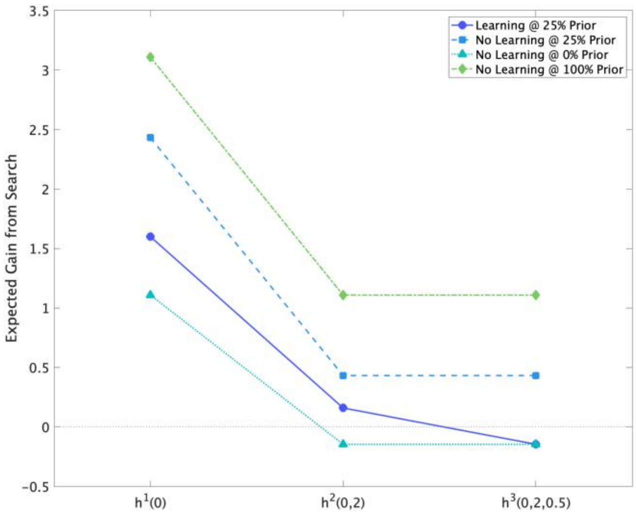
3.2. Test, Then Go Back

This difference in continuation behavior also has implications for which tested strategy is finally executed by the entrepreneur. Proposition 3 of Section 4 states a Theory-based entrepreneur does not always select the last tested strategy for execution, while a Practice-based entrepreneur always does so.

Because a Practice-based entrepreneur has a monotone search strategy, as soon as they locate a strategy above the optimal stopping threshold, that last strategy tested is the strategy implemented. Figure 3 plots this behavior using the same 25% prior on an exceptional distribution from our example. In Figure 3, $h^1(0)$ represents the starting point, where the entrepreneur just has an outside option of zero, with the "No learning @ 25% Prior" line representing a Practice-based entrepreneur. Initially, they expect to gain an improvement in payoff relative to their outside option of about 2.5 by searching for and testing a new strategy. If for the first draw, a strategy of value 2 is discovered, the incremental gain from continuation drops to about 0.5, represented by $h^2(0,2)$ in Figure 3. Next, suppose a strategy of 0.5 is discovered. This does not change their best-discovered strategy, so the gain from continuation remains 0.5 at $h^3(0,2,0.5)$. They effectively continue until they find a strategy that has a value of 2.5 or greater, and then execute their last found strategy.

By contrast, a Theory-based entrepreneur's expected gain from continuation will vary to a greater extent. Returning to Figure 3, we see that initially at $h^1(0)$, a Theory-based entrepreneur, represented by the "Learning @ 25% Prior" line, expects a gain of 1.6 from searching. We return to the difference between the initial valuation of the idea in Section 5; here we focus on how subsequent draws affect the continuation decision. The first draw of 2 lowers the expected return to another test from 1.6 to 0.16 at $h^2(0,2)$. Importantly, 2 could be equally generated by either an ordinary or exceptional distribution. Thus, the entrepreneur's initial prior of a 25% chance of exceptional distribution is too low and is revised upwards. This means that although the best-found strategy goes from zero to 2, the expected payoff from continuing search does not drop a commensurate amount. Next, a draw of 0.5 is made. As 0.5 is highly unlikely to come from the exceptional distribution, the Theory-based entrepreneur completely discounts their alternative theory and becomes confident their idea is ordinary. They acknowledge the previously tested strategy of 2 is an excellent draw from the ordinary distribution, and find nothing to gain from continuing to search, as $h^2(0,2,0.5)$ is negative 0.15. Continuing would only make them pay

Figure 3. (Color online) Sequence of Stopping



the search cost with a negligible chance of finding a draw greater than 2. As a result, they stop searching and execute the strategy that tested to have a value of 2. Thus, not only do they stop, but they also go back to their previous strategy. This test and go-back behavior is exhibited by Theory-based entrepreneurs but not Practice-based ones.

As an example, consider Google's early shifts in strategy for Internet search. The founders conjectured that Backrub, a technology that indexed and ranked the web, could be monetized. Their working theory held that licensing to existing Internet portals would prove lucrative, as Backrub improved the search experience for users. Under this working theory, the distribution of strategic payoffs was exceptional. An alternative theory held that Backrub would not be highly valued by Internet portals, as it encouraged users to leave the parent portal for other pages on the Internet. Under this alternative theory, the distribution of strategy payoffs was ordinary, as search advertising technology did not yet exist. Google initially tested a strategy to use Backrub to power its own website. Because the founders had strong beliefs in Backrub's licensing potential, they were unsatisfied with this initial strategy and tested other strategies. However, searching failed to yield a better option, as partnerships with or acquisitions by Altavista, Yahoo!, and Excite, three of the largest search portals of the period, were unattractive (Levy 2011). This caused Google's founders to discount their working theory and fall back on their alternative theory. Under this alternative theory, Google's previous strategy of using Backrub to power its own site was perhaps the best it could do. Hence, Google returned to a prior strategy, after disappointing results from testing new strategies, as predicted by our results on Theory-based entrepreneurs.

Note that this reversion behavior cannot be replicated for a Practice-based entrepreneur simply by changing the prior belief that the idea is exceptional. Figure 3 also plots the cases when the entrepreneur has a 0% and 100% prior of an exceptional distribution to illustrate this point. Therefore, models of entrepreneurial search that rely solely on heterogeneous priors without incorporating learning about the underlying distribution cannot account for an entrepreneur returning to a previously discovered strategy. However, a Theory-based entrepreneur who does learn in this way can justify cutting losses and stopping search after realizing that the best strategy for an idea has likely already been found.

3.3. Value of True Knowledge

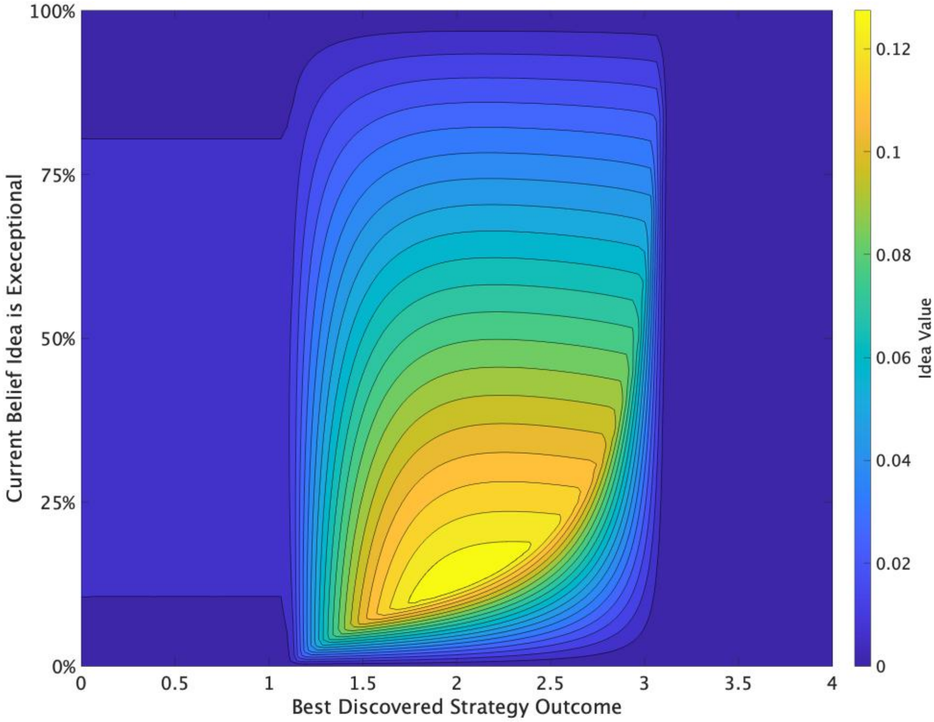
Lastly, we discuss Proposition 1 of Section 4. This result states that the Theory-based entrepreneur is always better off knowing which of their working and alternative theories is true and then making continuation decisions based on the resulting distribution. This implies a Theory-based entrepreneur would value advice from mentors and venture capitalists more than a Practice-based entrepreneur because such advice results in knowledge about which of their theories are correct.

By construction, the Practice-based entrepreneur is certain of their idea's distribution of strategies and, therefore would not value additional knowledge about the distribution of those strategies. In contrast, a Theory-based entrepreneur would be willing to pay to reduce the uncertainty surrounding the distribution of strategies. The value of knowing the true distribution derives from two sources: first, preventing unnecessary searches when the best-discovered strategy is, in fact, a good one conditional on the true distribution, and second, continuing search when the best-discovered strategy is poor conditional on the true distribution. This value varies with the entrepreneur's original belief and their current best option, as depicted in Figure 4 based on our example.

If the best-discovered strategy has a relatively high outcome, above 3, knowledge of the true distribution makes little difference for a Theory-based entrepreneur. Regardless of whether the idea is exceptional or ordinary, the entrepreneur should stop searching; therefore, learning about the distribution is irrelevant. Similarly, when the discovered outcome is relatively low, below 1, understanding the true distribution makes little difference to the Theory-based entrepreneur, as they will search regardless and thereby learn about the underlying distribution anyway. Hence, Theory-based entrepreneurs with intermediate best-discovered strategies will place higher value on knowing the true distribution.

This interplay between an ordinary and an exceptional idea is further elucidated through Figure 4's visualization of how the belief that an idea is exceptional affects the value of the true knowledge about the distribution. This value is low when the entrepreneur is fairly certain the idea is either ordinary or exceptional, the two extremes of belief. In Figure 4, when the entrepreneur's belief is lower than 5% or greater than 95%, they view

Figure 4. (Color online) Gain from Learning True Distribution



making a mistake in the search process, either stopping too soon or too late, as unlikely and therefore discount the value of knowing the true distribution of strategies. Overall, this suggests that Theory-based entrepreneurs, in general, will value the advice of experts such as venture capitalists, mentors, and industry veterans more than Practice-based entrepreneurs and that within Theory-based entrepreneurs, there can exist significant heterogeneity in how much they value that advice.

Such expert advice likely enabled Zappos's success in the online shoe space. Tony Hsieh, the founder of LinkExchange, was a key early investor in Zappos. At the time, Zappos was struggling with its online shoe strategy of drop shipping: getting shoe manufacturers to share their inventory information and ship shoes directly to customers on behalf of Zappos. Hsieh, who at the time ran a venture capital firm invested in several Internet startups, saw greater potential in Zappos than the founders did. They encouraged them to take a more aggressive strategy, having their own inventory and delivering phenomenal end-to-end customer service (Hsieh 2010). Hsieh's expert knowledge of what was possible on the Internet pushed Zappos into searching again, leading to its later success and Hsieh joining the company as its CEO.

4. General Model

We now demonstrate that the results for the illustrative example just examined hold in a general setting, in particular, for any set of distributions satisfying some regularity assumptions. Proofs for each proposition here are in the Appendix.

This section relies on the formal literature on search, which evaluates optimal search behavior under distributional uncertainty (Chow and Robbins 1963, McCall 1965). A key insight of that literature is that, in contrast to a search with a known distribution where the search only stops above a predetermined cut-off, uncertainty over the distribution results in a more complex stopping criterion, for example, leading to the possibility of stopping search after a sufficiently low draw (Rothschild 1974). The work built on Rothschild (1974) focuses primarily on identifying distributional uncertainty cases where a cutoff rule could nevertheless be established (Weitzman 1978, Adam 2001). This search theory has been applied to several domains outside of entrepreneurship, such as job search. Our model also builds on Rothschild (1974) but instead explicitly focuses on cases where the cutoff rule fails to hold, in contrast to much of the prior work in this area.

Our model involves an entrepreneur testing strategies $i \in \mathcal{S}$ sequentially at a cost per test of c. After testing each strategy, the entrepreneur decides whether to implement any tested strategy or continue testing by selecting a new strategy from $\mathcal{S}$. The distribution of strategy outcomes at each stage is not independent and not identical, represented by random variables $X_i \in \mathbb{R}_+$ whose probability distributions form a set $\mathcal{D}$. Having conducted n tests, the entrepreneur can choose to implement a strategy with the highest realization x_i amongst the n tested strategies. This results in an expected payoff of:

$$y = \max\{x_1, \ldots x_n\} - nc \tag{1}$$

We impose the following regularity assumptions on the set of distributions.

Assumption 1. *There exists random variables $\overline{X}$ and $\underline{X}$ with distributions such that $\overline{X}$ first-order stochastically dominates all marginal distributions $Pr(X_i = x_i | X_1 = x_1, \ldots, X_{i-1} = x_{i-1})$ generated from $\mathcal{D}$ and $\underline{X}$ is similarly dominated by all marginal distributions generated from $\mathcal{D}$.*

Assumption 2. *$\overline{X}$ and $\underline{X}$ have finite first moments.*

Assumption 3. *$\overline{X}$ has a finite second moment.*

Assumptions 1 and 2 ensure $y < \infty$ while Assumption 3 additionally establishes that $E[y] < \infty$, both necessary for the value of the entrepreneur's idea to be finite. Essentially, this implies an entrepreneur's search process does eventually stop. Note that although we formulate search as a maximization across all the draws as random variables, we can arbitrarily add an initial outside option set as x_0 without changing any of our results.

The next assumption formally defines a Theory-based entrepreneur.

Assumption 4. *A Theory-based entrepreneur's beliefs about the true distribution of strategy payoffs for the idea can be represented by an element of a concave set Λ of probability measures over $\mathcal{D}$.*

Definition 1. A Theory-based entrepreneur updates beliefs about the true distribution of strategy payoffs for an idea after each search while a Practice-based entrepreneur believes that the distribution is fixed during search.

Assumption 4 ensures that a Theory-based entrepreneur can find a new belief after search that is consistent with their prior beliefs and the result of that search.

With these assumptions, we can state the following result that confirms that learning about distributions is valuable to a Theory-based entrepreneur. (Note that, by assumption, such learning has no value to a Practice-based entrepreneur.)

Proposition 1. *Under Assumptions 1 to 4, the value of an idea weakly increases when the idea's true distribution is revealed.*

Proposition 1 confirms that a Theory-based entrepreneur would value an idea more if they knew the true distribution of the idea's value. Such information is valuable in two respects. First, the true distribution may be less favorable than the distribution implied by the entrepreneur's prior. The revelation would allow search to be terminated earlier, lowering the overall cost of search with a proportionality smaller drop in expected payoff, yielding a net benefit. Alternatively, the true distribution may be more favorable than the entrepreneur's prior implied. The revelation would then prevent premature stopping. Hence, knowing the distribution can only improve the value of the idea to the entrepreneur.

Next, we impose a set of parametric restrictions to allow us to characterize entrepreneurial strategy. Let $\mathcal{D}$ be indexed by θ and the distribution of beliefs over those distributions, Λ, in turn, be indexed by λ. After each search, λ gets updated conditional on the discovered strategy's value x_i through the function $\pi(\lambda, x)$

Assumption 5. *The family of distributions $\mathcal{D}$ displays first-order stochastic dominance in θ, and the family of distributions Λ displays first-order stochastic dominance in λ.*

Assumption 6. *Belief λ conditional on discovering a strategy of value x updates through $\pi(\lambda, x)$, which is increasing in both its arguments.*

Assumption 7. *Given current belief λ, there exists discoverable strategies with outcomes x', and x'' such that $x' < x''$ and $\lambda' \equiv \pi(\lambda, x') < \lambda'' \equiv \pi(\lambda, x'')$*

Assumptions 5 and 6 ensure the expected value of an idea is weakly increasing in outcome z and parameter λ, as well as weakly decreasing in cost c. Assumption 7 states that the necessary variation in belief may result from the next search.

This leads to our first result regarding the monotonicity of search:

Proposition 2. *Under Assumptions 1–7, there exists a discovered strategy outcome z and search cost c such that it is optimal to stop after the discovery of a lower outcome strategy but continue searching after the discovery of a higher outcome strategy.*

For Theory-based entrepreneurs, search has two effects on the expected gain from additional search: a best outcome effect and a learning effect. The best outcome effect can only make the additional search less valuable; if a newly discovered strategy has a higher outcome than any previously discovered strategy, the entrepreneur is less likely to conduct further search simply because the possibility of finding a better outcome than the new best has been reduced. When the distribution of outcomes is known with certainty, that is, for Practice-based entrepreneurs, this is the only effect of search, resulting in the simple cutoff-stopping rule. However, for Theory-based entrepreneurs, the learning effect is also present. Search provides information about the likelihood strategies follow a particular distribution and, therefore, insight into whether a particular theory is true. Proposition 2 states when the outcome of a strategy suggests a poor draw from a good distribution rather than a good draw from a poor distribution, the learning effect can outweigh the best outcome effect, increasing the value of search and therefore resulting in additional search.

In addition, the same set of assumptions allows for the reverse logic: termination when the outcome of a strategy suggests a good draw from a poor distribution rather than a poor draw from a good distribution.

Proposition 3. *Under Assumptions 1 to 7, there exists a best-discovered strategy outcome z, and search cost c such that the best strategy outcome upon the termination of search will not be the last discovered strategy.*

Proposition 3 is the result of the downward revision of an entrepreneur's beliefs about the idea's value. After attaining a surprisingly good draw leading to an additional search, the next draw might be relatively poor. This makes the Theory-based entrepreneur realize the previous draw was the best they are likely to get, causing a reversion to that previously discovered strategy and the termination of search. The entrepreneur effectively learns from failure.

5. Assessing the Objective and Subjective Valuation of Ideas

An entrepreneur's mindset affects their valuation of ideas. This can lead to an entrepreneur's idea valuation being *objectively* more or less correct, which can be helpful in divining the performance implications of each approach to entrepreneurial decision making. However, it requires strong assumptions about what is the objectively "true" theory, which may be difficult in many empirical settings. In addition, the mindset also affects the *subjective* valuation of an idea under weaker assumptions of our paper's general model. This allows us to illustrate how differences in subjective valuation due to an entrepreneur's mindset lead to different continuation decisions. In empirical settings, such differences can help uncover the mindset being used by the entrepreneur in their search. In this section, we review these objective and subjective differences in idea valuation due to entrepreneurial mindset.

5.1. Objective Valuation

To start, consider the case where the Theory-based entrepreneur is ex-ante correct: they have properly characterized their working theory and alternative theories as well as each theory's distributional outcomes and the likelihood of being true. The Practice-based entrepreneur starts with the same distributional belief about outcomes but ignores the information generated from the search process. Hence, the difference between the two types of entrepreneurs amounts to whether learning takes place or not. As a result, the Practice-based entrepreneur deviates from the optimum Bayesian stopping rule, leading to a lower idea value because in some cases the Practice-based entrepreneur will search too often, while in others they will not search enough.

To illustrate, recall that in Section 3's example, there was a 25% probability that the idea is ordinary, having strategies with payoffs distributed $N(1, 1/2)$, and a 75% probability that the idea is exceptional with strategies whose payoffs are distributed $N(3, 1/2)$. Because the Practice-based entrepreneur does not learn over time, the stopping cutoff remains unchanged, at about 1.6, after every strategy draw. This leads to two inefficiencies.

First, when the actual distribution is $N(1, 1/2)$, the Practice-based entrepreneur draws too often given the cost of search. Only 12% of draws will be above 1.6, which given a search cost of 0.15, means that in expectation the entrepreneur will make several draws before finding a strategy with a payoff above 1.6. These repeated search costs add up, leading to the overall expected value of the idea being just 0.55 once search costs are accounted for. In contrast, if the entrepreneur was aware that the actual distribution is $N(1, 1/2)$, the entrepreneur would optimally have a stopping cutoff rule of 1.1 rather than 1.6. This would lead to fewer searches on average and a higher expected value of about 1.1 instead of 0.55.

Second, if the idea is exceptional with strategy payoffs drawn from an $N(3, 1/2)$ distribution, stopping after uncovering a strategy of payoff 1.6 is premature, as over 99% of all draws will satisfy this cutoff. Hence the Practice-based entrepreneur stops too early, resulting in an expected idea value of 2.85. For an $N(3, 1/2)$ distribution, the Practice-based entrepreneur should optimally have a higher cutoff of 3.1 instead of 1.6. This higher cutoff would lead to more searches and a higher expected value of about 3.1 instead of 2.85 after search costs are accounted for. These two deviations from optimal behavior, continuing search too long under an ordinary idea and halting search too soon under an extraordinary idea, result in the ex-ante value of the idea being just 1.12 (i.e., $0.55*0.75 + 2.85*0.25$).

Meanwhile, the Theory-based entrepreneur learns about the idea's underlying quality during search and updates their cutoff appropriately. The change in cutoff enables the Theory-based entrepreneur to avoid search costs when search is futile but continue searching when the search cost is justified. Consider how the two underlying distributions overlap in Figure 1(a). For draws lower than about 1.5, the Theory-based entrepreneur almost certainly knows the underlying distribution if ordinary, and therefore will apply the optimal stopping cutoff of 1.1. For draws above 2.5, the converse holds, and the entrepreneur will apply the optimal cutoff of 3.1 for the exceptional distribution. Hence, other than a small band around the value of 2 having a relatively low probability mass (see Figure 1(b)), the Theory-based entrepreneur would gain significant information about the underlying distribution upon the first draw. After that first draw, the entrepreneur will likely make optimal decisions based on the "true" distribution. This means the Theory-based entrepreneur will make fewer suboptimal decisions, and yields a higher expected payoff from the idea than the Practice-based entrepreneur, 1.67.

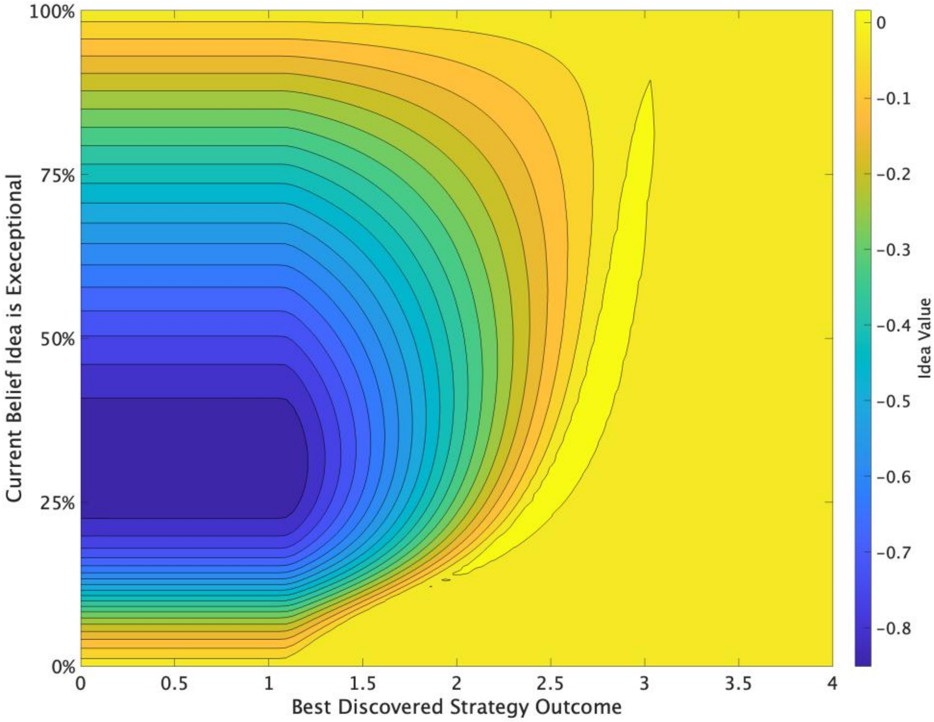
However, empirically observable differences in performance between entrepreneurs of the two mindsets are a more open question for several reasons. First, the Theory-based entrepreneur's collection of beliefs and confidence in those beliefs may be inaccurate, preventing the Theory-based entrepreneurs from converging to the 'true' distribution as in the previous paragraph. Second, the differences in an idea's value between theory-based and practice-based mindsets can lead to differences in the characteristics of entrepreneurs who choose to search for strategies, causing selection bias issues in an empirical setting. Third, switching between working theories and alternative theories can incur additional costs not incorporated in our model, as a lack of commitment to a particular theory might negatively affect employee effort (Wang and Lim 2008) or resource allocation (Chavda 2023). Fourth, the costs of experimentation, certain market conditions, or entry barriers may not be observable, making it impossible to generate a clear causal link between a theory and its corresponding distribution of strategic outcomes which would hinder theory-based decision making. Finally, some Theory-based entrepreneurs may opt to behave as Practice-based ones due to an excessively high cost of search relative to the potential gains in distributional information (Camuffo et al. 2024). As a result, in this paper, we have emphasized deriving empirically observable patterns in search decision making which reveal the mindset of entrepreneurs as opposed to objectively valuing one approach over the other.

5.2. Subjective Valuation

Although gauging objective valuations is difficult for the above-mentioned reasons, we can use our model to contrast the subjective valuations of entrepreneurial ideas under different mindsets. In the example used for Section 3 (see Figure 3), the Practice-based entrepreneur subjectively valued the idea higher, at 2.5, than a Theory-based entrepreneur would, at 1.6. However, the higher valuation by the Practice-based entrepreneur is not a general statement, it is conditioned on the model parameters. Figure 5 plots the full range of modeling parameters and the corresponding difference in subjective idea valuation between Practice-based and Theory-based entrepreneurs. Using the continuation decision, we will provide some intuition as to why in some areas the idea is valued higher by Practice-based entrepreneurs and why in other areas Theory-based entrepreneurs hold a higher value for the idea.

At lower best-discovered strategies, the Theory-based entrepreneur subjectively values the idea less than the Practice-based one. As the cost of search rises, Theory-based entrepreneurs will be deterred from searching

Figure 5. (Color online) Difference Between Theory-based and Practice-based Idea Values



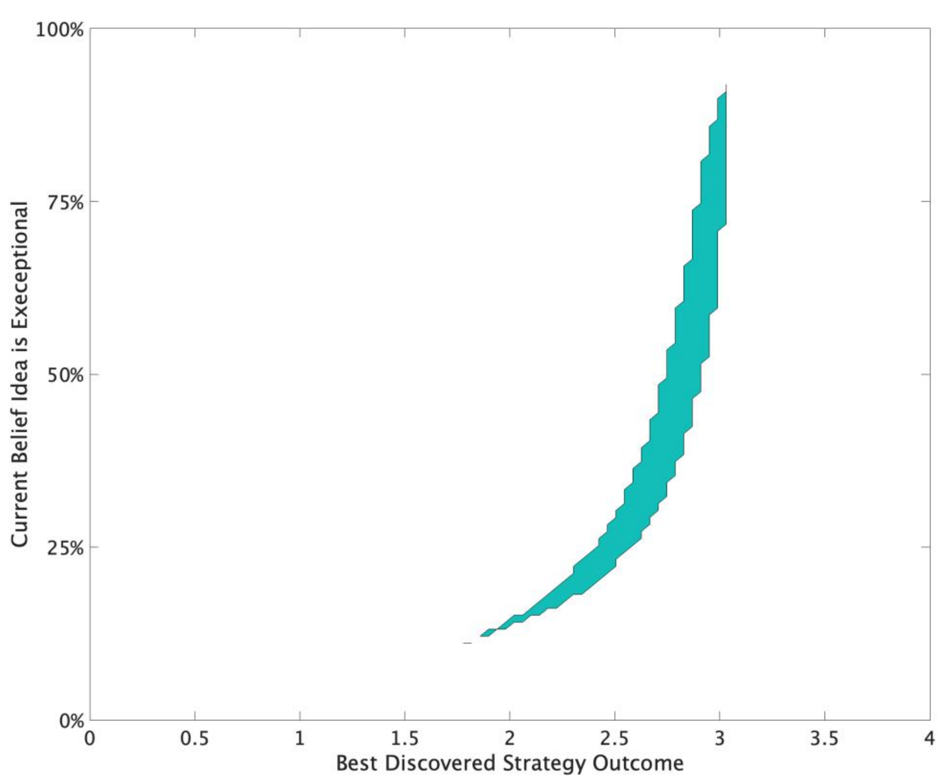
before Practice-based ones would be. This is related to the potential nonmonotonicity of the Theory-based entrepreneur's search strategy. For a Practice-based entrepreneur, additional draws do not alter their beliefs regarding the overall distribution of strategy outcomes. Therefore, if a draw is for a relatively low value, they will keep searching and testing new strategies: the value of the idea remains unchained after such low draws. By contrast, a Theory-based entrepreneur receiving low-value draws will update their beliefs regarding the distribution – in this case, placing more weight on the idea of being ordinary rather than exceptional. Thus, they are more likely to expect to stop searching after receiving low draws. This both lowers the frequency we would observe the Theory-based entrepreneur searches relative to the Practice-based entrepreneur and lowers the Theory-based entrepreneur's value of the idea relative to the Practice-based entrepreneur.

To help illustrate why this is the case, let us briefly suppose that the two relevant distributions for X_i are $N(0, 0)$ and $N(1, 0)$, respectively. In other words, the "distributions" are really point values of 0 or 1. Assume the cost of search, $c \in \mathbb{R}_+$, and the prior likelihood the distribution is exceptional, $p \in (0,1)$, is such that both types of entrepreneurs will search at least once and stop once a draw of 1 is received. The expected return of the initial draw is therefore $0 \cdot (1-p) + 1 \cdot p - c = p - c > 0$. In this setup, a Theory-based entrepreneur will believe they know the true distribution after a single draw and stop. On a draw of 0, the Theory-based entrepreneur believes for certain that the value of all future draws is zero and therefore that no additional search is warranted. On a draw of 1, there is no possibility of doing better given the positive cost of search c, so search also terminates. Hence, the ex-ante subjective value of the idea for the Theory-based entrepreneur, $E_T[v]$, is also $p - c$. By contrast, although a Practice-based entrepreneur will also stop at a draw of 1 with probability p, they will continue searching after a draw of 0 since the following draw will be identical to the initial draw, having an expected payoff of $p - c > 0$. This implies the value of the idea conditional on a draw of zero for the Practice-based entrepreneur, $E_P[v|0]$, is greater than zero. Hence, the ex-ante subjective value of the idea for the Practice-based entrepreneur is $E_P[v] = E_P[v|0] \cdot (1 - p) + 1 \cdot p - c > p - c = E_T[v]$, exceeding the subjective value of the idea for the Theory-based entrepreneur.

In the region where the best-discovered strategy is sufficiently high, both types of entrepreneurs value the idea identically. Even if the idea is exceptional, neither entrepreneur chooses to search since the cost of search outweighs any potential gain. Hence, their subjective valuations are aligned since they effectively both opt for their previously discovered strategy rather than conduct search.

Interestingly, there is a region where a Theory-based entrepreneur subjectively values the idea more than a Practice-based, highlighted in Figure 6. For the pairs of

Figure 6. (Color online) Region Where Theory-based Entrepreneur Values Idea More than Practice-based Entrepreneur



beliefs and best-discovered strategies in this region, the Practice-based entrepreneur would stop, accepting that the best-discovered strategy as the cost of search does not justify an additional draw. However, a Theory-based entrepreneur greatly benefits from the incremental learning to be gained from an additional search, as they are uncertain about whether the distribution is normal or exceptional. By paying the cost of an additional search, they will resolve that uncertainty. On the one hand, the search cost might be wasted if the idea is normal, as the entrepreneur will afterward terminate search and execute their previously best-discovered strategy. However, if the next draw has an outcome that is unlikely to come from the normal distribution, this opens the possibility for even further search to exploit the exceptional distribution. This potential upside outweighs the risk of a single unnecessary search if the idea is in fact normal. As a result, the Theory-based entrepreneur conducts more search and subjectively values the idea more than a Practice-based entrepreneur. Notably, this theory-based continuation decision is grounded in our Proposition 3 finding about reversing to a previous strategy when the uncertainty resolves in the distribution to be normal.

This example highlights two competing factors that affect the relative valuation of Theory-based and Practice-based entrepreneurs. The fact that Theory-based entrepreneurs can downgrade their beliefs about the distribution of strategy outcomes makes continuation slightly less likely in some cases. But in others, the fact that Theory-based entrepreneurs can call back on their previously best-discovered strategy can also make their continuation decision more common and in a sense exploratory, attempting search on the chance of being pleasantly surprised with the outcome. The above discussion highlights how the subjective valuation of an idea differs between Theory-based and Practice-based entrepreneurs and how that subjective valuation affects search behavior. This is a step toward understanding outcomes, that is, under what conditions a Theory-based entrepreneur will fare better than a Practice-based one and visa-versa, as these subjective differences will play into the objective success of each type of entrepreneur, which will vary depending on what the "true" nature of the world is assumed to be and which ideas each type of entrepreneur selects to pursue.

6. Conclusion

In this paper, we show a theory-based approach to the entrepreneurial search for strategies differs from a practice-based approach in several ways. Theory-based entrepreneurs are more likely to continue search after discovering a strategy with an abnormally large payoff as they interpret their success as indicative of the presence of even better strategies, rather than simple luck. They also may revert to a previous strategy if they learn they are wrong about the existence of even better strategies in contrast to Practice-based entrepreneurs who always stop and execute the last discovered strategy. Moreover, Theory-based entrepreneurs have one additional reason to value the advice of outside experts such as venture capitalists, mentors, or industry veterans: such experts can prove their worth by revealing an idea's true distribution of strategy outcomes.

Our findings contribute to the literature on theory-based entrepreneurship by highlighting how the theory-based view can shape behavior beyond the phase of entrepreneurial theorizing when entrepreneurs shape their beliefs(Felin and Zenger 2009). Even after the formation of those beliefs and resulting theories that are used to infer consequences, theory can lead to meaningful changes in entrepreneurial behavior, much like Camuffo et al. (2024) finds for low-frequency high-impact decisions with general managerial decision making. In our paper, we explore how theory influences one key and well-recognized step in the entrepreneurial process, the search for strategies (Alvarez and Barney 2007), but theory's influence should not stop there. We believe having a theory-based view can potentially alter many aspects of the discovery and exploitation of opportunities (Shane and Venkataraman 2000), including the identification of promising domains (Ward 2004, Fiet et al. 2005, Baron and Ensley 2006, Fiet 2007, Fiet and Patel 2008, Gruber et al. 2008), the interplay between learning and entrepreneurial action (Gaglio and Katz 2001, Choi et al. 2008, Agrawal et al. 2021, Gans 2023, Rapp and Olbrich 2023), the valuation of opportunities (Norton and Moore 2002, Chen et al. 2018, Camuffo et al. 2024), and planning to execute on a specific opportunity (Delmar and Shane 2003, Shane and Delmar 2004). We see entrepreneurial learning to be less structured, as suggested by recent empirical studies (Arikan et al. 2020, Rapp and Olbrich 2023) that find learning occurs across a wide variety of entrepreneurial activities, including entrepreneurial search as studied here. And if learning happens throughout the entrepreneurial process, theory has a role to play as it helps entrepreneurs understand and react to new information. Hence, we see a strong potential for the theory-based view to contribute to our understanding of entrepreneurship by fleshing out how the mindset of the entrepreneur can broadly affect decision making and outcomes.

Since the search for strategies is fundamentally a form of experimentation, our paper additionally contributes to the entrepreneurial literature by providing a model framework that can be used for other forms of entrepreneurial experimentation. Within the context of entrepreneurial search, we demonstrate the value of employing a middle-ground between two historical approaches: one that assumes the existence of the aforementioned cut-off decision rule and another that assumes a form of Knightian uncertainty that allows for events literally outside the realm of possibility. Studying cases where a monotonic cut-off rule exists is of course important and provides valuable insight into entrepreneurial behavior and experimentation (Mosakowski 1997, Angus 2019). Moreover, approaches modeling pure Knightian uncertainty can help us understand decision making under extreme levels of uncertainty (Chou and Talmain 1993, Nishimura and Ozaki 2004, Schröder 2011, Karni and Vierø 2017, Cerreia-Vioglio et al. 2020). However, we argue that our knowledge of entrepreneurial behavior can be further enhanced by allowing for nonmonotonic stopping rules in other entrepreneurial decision contexts while stepping back from completely unbounded outcome sets.

Our findings also contribute to the growing literature on entrepreneurial strategy: how optimal decisions and behaviors for entrepreneurs differ from managers in established enterprises due to the nature of entrepreneurship. In our case, the uncertainty surrounding entrepreneurship in new industries is what drives our results and makes them unique to entrepreneurial settings. This is fundamental to the literature studying the choices entrepreneurs need to make when entering markets with established incumbents or when deciding between strategies that cannot be easily ranked (Gans et al. 2018, 2019, 2024). Our paper underscores the potential in future work that characterizes what is unique about entrepreneurial settings and explores the consequent implications for optimal entrepreneurial behavior. In doing so, we bridge the gap between prior work on entrepreneurial search theory, which has mostly been concerned with how search should be conducted given an existing theory (e.g., Agrawal et al. 2021) and the theory-based view of strategies, which is concerned with divining the truth among multiple theories.

Finally, this study has both policy and pedological implications. Entrepreneurs differ from each other in numerous ways, including their demographic background, work history, and personal networks (Evans and Leighton 1989, Hurst and Lusardi 2004, Gompers et al. 2005, Sørensen 2007, Lerner and Malmendier 2013). These differences are material in that they have been shown to influence entrepreneurial outcomes, affecting the success or failure of startups. Of particular interest to scholars focused on policy or pedagogy related to entrepreneurship are the characteristics that can change, as altering those characteristics, either through government policy or individual instruction, can improve entrepreneurial outcomes and the economy-wide benefits known to be associated with entrepreneurship, such as innovation and job growth (Gans et al. 2002, Decker et al. 2014). This study focuses on one of these potentially mutable entrepreneurial characteristics, the mindset of the entrepreneur, and thereby adds to our knowledge of how to improve entrepreneurial activity.

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Appendix A. Proofs

A.1. Preliminary Results

Lemmas A.1 and A.2 are required for Propositions 1 to 3. Lemma A.1 proves search stops at a finite value. Lemma A.2 adds that the value is in expectation also finite.

Lemma A.1. *Under Assumptions 1 and 2, search stops at a finite value.*

Proof. The probability y of Equation (1) is less than some constant u and is therefore finite can be written as the intersection of all events where the draws of random variables were bounded by u plus the cost of search:

$$\Pr(y \leq u) = Pr(x_1 < u + c, x_2 < u + 2c, \ldots)$$

Using marginal distributions, this becomes:

$$\Pr(y \leq u) = \prod_{n=1}^{\infty} \Pr(x_n \leq u + nc | x_1 \leq u + c, \ldots, x_{n-1} < u + (n-1)c)$$

For each n we know based on Assumption 1 and the definition of first-order stochastic dominance (see for example Shaked and Shanthikumar (2007) (1.A.1)):

$$\Pr(\underline{x} \leq u + nc) \geq Pr(x_n \leq u + nc | x_1 \leq u + c, \ldots) \geq \Pr(\overline{x} \leq u + nc)$$

since at best the draws will be from $\overline{X}$ and at worst from $\underline{X}$. From Chow and Robbins (1963, lemma 8), we know the stopping problem with independent identical distributions $\underline{X}$ and $\overline{X}$ having finite first moments (Assumption 2) has solutions $\underline{y} < \infty$ and $\overline{y} < \infty$ so can write:

$$\Pr(\underline{y} \leq u) = \prod_{n=1}^{\infty} \Pr(\underline{x}_n \leq u + nc) \geq Pr(y \leq u) \geq \prod_{n=1}^{\infty} \Pr(\overline{x}_n \leq u + nc) = Pr(\overline{y} \leq u) \tag{A1}$$

By the squeeze theorem this implies $\Pr(y \leq u) = 1$ since both $\Pr(\underline{y} \leq u) = 1$ and $\Pr(\overline{y} \leq u) = 1$. □

Lemma A.2. *Under Assumptions 1, 2, and 3, the expected value of search is finite.*

Proof. We can write:

$$E[y] = \int_0^{\infty} (1 - \Pr(y < t))dt - \int_0^{\infty} \Pr(y < t)dt$$

From (A1) and Assumption 1 and the definition of first-order stochastic dominance, we know:

$$\int_0^\infty (1-\Pr(y<t))dt - \int_0^\infty \Pr(y<t)dt \leq \int_0^\infty (1-\Pr(\overline{y}<t))dt - \int_0^\infty \Pr(\overline{y}<t)dt$$

where $\overline{y}$ is drawn from $\overline{X}$. Therefore, $E[\overline{y}]$ is an upper bound for $E[y]$. By Assumptions 2 and 3, we know $E[\overline{y}]$ has a finite upper bound, see Chow and Robbins (1963, theorem 3). Similarly, $E[\underline{y}]$ where $\underline{y}$ is drawn from $\underline{X}$ is a lower bound for $E[y]$. So $E[y]$ must be finite. □

Corollary A.1. *Lemmas A.1 and A.2 hold when an outside option is present.*

Proof. Add a random variable X_0, which always has its outcomes mapped to the constant outside option z. Let stopping happen at stage $n = 0$ if the outside option is taken without any draws. Since X_0 is independent of the other draws, we can write

$$\Pr(y \leq u) = Pr[x_1 \leq u + c, x_2 \leq u + 2c, \ldots]Pr[z \leq u]$$

If $z > u$, we can always pick another finite $u' > z$ since z is finite, making $\Pr[z \leq u] = 1$ and allowing us to follow the rest of Lemma A.1 proof that $y < \infty$. The same logic applies to Lemma A.2 as well, using the above formulation of $\Pr(y \leq u)$. □

A.2. Proof of Proposition 1

We will show that the proposition follows from the concavity of Bayesian risk. We loosely conform to the notation used in Wijsman (1970) and assume the conditions for Lemma A.2 hold so the value functions below exist.

Let each θ in a set $\mathcal{D}$ index the possible distributions an idea's strategy may have with the measure $\theta(dx)$ representing the probability a strategy has value x given the distribution is θ. Let the current best-discovered strategy have value z. Conditional the decision maker knowing a specific θ^* is true, the value of the idea would be:

$$v(z;\theta^*) = \begin{cases} z, & \text{if } z \geq \int v(\max\{z,x\};\theta^*)\theta^*(dx) - c \\ \int v(\max\{z,x\};\theta^*)\theta^*(dx) - c, & \text{otherwise} \end{cases} \tag{A.2}$$

In contrast, suppose that while the true distribution was θ^*, the decision maker only has beliefs about θ^*, allowed to evolve after each draw. Let Λ be a concave set of probability distributions over $\mathcal{D}$, as per Assumption 4. Each element λ of Λ represents the decision maker's beliefs about the likelihood each element of $\mathcal{D}$ is the correct strategy distribution for an idea, represented by the measure $\lambda(d\theta)$. After each search, the decision maker's beliefs update according to $\pi(\lambda, x)$, where x is the value of the discovered strategy. The decision maker values search therefore as:

$$\hat{v}(z,\lambda) = \begin{cases} z, & \text{if } z \geq \int\int \hat{v}(\max\{z,x\},\pi(\lambda,x))\theta(dx)\lambda(d\theta) - c \\ \int\int \hat{v}(\max\{z,x\},\pi(\lambda,x))\theta(dx)\lambda(d\theta) - c, & \text{otherwise} \end{cases} \tag{A.2}$$

In this case, a decision maker having prior λ would gain the following value from the idea:

$$v(z,\lambda;\theta^*) = \begin{cases} z, & \text{if } z \geq \int\int \hat{v}(\max\{z,x\},\pi(\lambda,x))\theta(dx)\lambda(d\theta) - c \\ \int v(\max\{z,x\};\theta^*)\theta^*(dx) - c, & \text{otherwise} \end{cases} \tag{A.3}$$

Note Equation (A.3) differs from Equation (A.2) only in the decision rule for which payoff is selected at each stage, not the actual payoff itself. Equation (A.3) uses the decision maker's current beliefs about the value of search to determine whether search stops or continues. As Equation (A.2) optimizes this decision by selecting the maximum payoff, Equation (A.3) must necessarily be weakly less than Equation (A.2), as under Equation (A.3) the decision maker may stop when continuing search would be optimal or continue search when stopping would be optimal.

We can write the value placed on an idea by the decision maker as the expected value of Equation (A.3) given the probability distribution λ over the possible distributions $\mathcal{D}$:

$$v(z,\lambda) = \int v(z,\lambda;\theta)\lambda(d\theta) = E[v(z,\lambda;\theta)] \tag{A.4}$$

Contrast this to the value of the idea if that decision-maker with prior belief λ was given knowledge of the true distribution. With the true distribution, the decision maker can follow the optimum decision rule of Equation (A.2) rather than (A.3):

$$v(z) = \int v(z;\theta)\lambda(d\theta) = E[v(z;\theta)] \tag{A.5}$$

As the integrand of Equation (A.4) is weakly less than the integrand of Equation (A.5) while both Equation (A.4) and Equation (A.5) share the same measure, it follows that Equation (A.4) must be weakly less than Equation (A.5). Therefore, a decision maker must be weakly willing to pay for true knowledge of the strategy distribution for an idea, as this weakly increases the value of their idea from Equation (A.4) to Equation (A.5).

A.3. Lemma 3: Comparative statics Under Assumptions 1 to 6

We now derive some comparative statics results used in the proofs of Propositions 2 and 3 below. Smith and McCardle (2002) provides in their Proposition 5 a framework to determine the comparative statics for dynamic programming problems such as the value function of Equation (1). Our setup can be described in their framework as:

- Each decision-making stage is indexed by k with $k = 0$ being the last stage
- Possible actions a_k at each stage k are either *stop* or *continue*
- A state vector $\boldsymbol{x}_k$ containing four elements:
  – The state s_k of the search at stage k can either be *run* if search is ongoing or *halt* if search has terminated
  – The current best option z_k, initialized at 0
  – The current belief about the distribution λ_k
  – The cost of search c_k, which is constant in our setup
- A reward function $r_k(a_k, \boldsymbol{x}_k)$ is as follows

	$s_k = halt$	$s_k = run$
$a_k = stop$	0	z_k
$a_k = continue$	0	$-c_k$

- A transition function for the state vector $\tilde{\boldsymbol{x}}_{k-1}(a_k, \boldsymbol{x}_k)$ that accounts for a random element, in our case the discovered item y_k from search at stage k

$\boldsymbol{x}_k$	a_k	$\tilde{\boldsymbol{x}}_{k-1}$
$s_k = run$	*stop*	*halt*
	continue	*run*
$s_k = halt$	*stop*	*halt*
	continue	*halt*
z_k	*stop*	$\max\{z_k, y_k\}$
	continue	$\max\{z_k, y_k\}$
λ_k	*stop*	$\pi(\lambda_k, y_k)$
	continue	$\pi(\lambda_k, y_k)$
$-c_k$	*stop*	$-c_k$
	continue	$-c_k$

- *Increasing* as the closed convex cone property under consideration

Smith and McCardle's basic intuition is that each stage of a dynamic program can be broken down into a payoff or reward for that stage plus an expected value of continuation. As the combination of increasing functions is also increasing, the dynamic program will be increasing in its arguments as long as the reward and continuation value are both non-decreasing, conditional on the action taken at each stage. The reward function in our setup is weakly increasing in $-c_k$ and z_k, regardless of the action taken. λ_k has no effect on the reward function, so we can also refer to it as weakly increasing. Therefore, the first part of their requirements are met.

To show the continuation value is increasing, an increase in the parameters $\boldsymbol{x}_k$ must cause a FOSD shift in the distribution of $\tilde{\boldsymbol{x}}_{k-1}$. First, consider increasing z_k from z_k' to z_k''. The probability of getting a value of z_{k-1} below z_k' is zero for both cases. However, there is some mass between z_k' and z_k'' for the distribution conditional on z_k' that is missing for the distribution conditional on z_k''. For values of z_{k-1} above z_k'', both have the same cumulative density function. Therefore the difference in mass of z_{k-1} between z_k' and z_k'' implies $\tilde{z}_{k-1}(z_k'') \underset{FOSD}{>} \tilde{z}_{k-1}(z_k')$. As $\tilde{z}_{k-1}$ is the only future state affected by z_k, this is sufficient to show an increase in z_k produces a FOSD shift in $\tilde{x}_{k-1}$.

In addition, the distributions of λ_{k-1} and z_{k-1} must be FOSD in λ_k, since both are a function of λ_k. Increasing λ_k will cause a FOSD shift in y_k due to Assumption 5, following theorem 1.A.6 in Shaked and Shanthikumar (2007). Since z_{k-1} is an increasing function of y_k, this will cause a corresponding FOSD shift in $\tilde{z}_{k-1}$ due to theorem 1.A.3 in Shaked and Shanthikumar (2007).

Increasing λ_k has an effect on both the λ_k parameter in $\pi(\lambda_k, y_k)$ and the distribution of y_k, so both aspects need to be accounted for. For any $\lambda_k'' > \lambda_k'$, we know $\pi(\lambda_k'', y_k) > \pi(\lambda_k', y_k)$ for each y_k due to Assumption 6. Theorem 1.A.17 in Shaked and Shanthikumar (2007) gives us therefore that the distribution of $\pi(\lambda_k'', y_k)$ will be greater than $\pi(\lambda_k', y_k)$ conditional on y_k be distributed conditional on λ_k'. Theorem 1.A.6 of Shaked and Shanthikumar (2007) provides that under Assumption 5 the distribution of $\tilde{y}_k$ is FOSD in λ_k. As $\pi(\lambda_k'', y_k)$ is an increasing function of y_k under Assumption 6, we must therefore have the distribution of $\pi(\lambda_k'', y_k)$ conditional on $\tilde{y}_k$ being distributed conditional on λ_k'' FOSD dominating the distribution conditional on λ_k'. Therefore, the distribution of $\pi(\lambda_k, y_k)$ conditional on λ_k'' overall is FOSD over the distribution conditional on λ_k', and more generally the distribution of $\tilde{\lambda}_{k-1}$ is FOSD increasing in λ_k.

Finally, as $\tilde{c}_{k-1}$ is trivially distributed with a single point mass at c_k, increasing $-c_k$ also leads to a FOSD shift in the next period distribution.

As a last condition for v_k to be non-decreasing in z_k, λ_k, and $-c_k$, we need v_k to exist as $k \to \infty$. This is given by Lemma A.2, as v_∞ is essentially y of Equation (1).

In addition, when recall is not allowed, the transition function for z_k is simply y_k. Therefore, without recall, the same comparative statics as above trivially hold.

Moreover, when learning does not take place, the transition function for λ_k returns simply λ_k, so again, the same comparative statics hold.

A.4. Proof of Proposition 2

Following Assumption 7's terminology, suppose draw x'' is taken. Given the previous best option z and existing beliefs λ, define:

$$c^* \equiv \int v(\max\{z, x'', x\}, \pi(\lambda'', x)) f(x; \lambda'') dx - \max\{z, x''\}$$

so at a cost, c^*, the decision maker is indifferent between stopping and continuing after drawing x'', making continuing search optimal, fulfilling the second part of the proposition.

Assumption 7 provides there exists an $x' < x''$ such that $\pi(\lambda, x') < \pi(\lambda, x'')$. Above we showed that the value function is decreasing in λ and therefore

$$c^* > \int v(\max\{z, x', x\}, \pi(\lambda', x)) f(x; \lambda') dx - \max\{z, x'\}.$$

This implies stopping occurs at x', fulfilling the first part of the proposition.

A.5. Proof of Proposition 3

Let $z = x''$ and similarly to Proposition 2 define the cost as the indifferent point between continuing and stopping search after drawing x'' when z already equals x'':

$$c^* \equiv \int v(\max\{x'', x\}, \pi(\lambda'', x)) f(x; \lambda'') dx - x''.$$

With this cost of search, if x' is instead drawn when $z = x''$, stopping occurs due to Assumption 7, with the searcher reverting to the strategy having outcome x'' which is less than x'.

$$c^* > \int v(\max\{x'', x\}, \pi(\lambda', x)) f(x; \lambda') dx - x''.$$

Endnotes

[1] Advance Monthly Retail Trade Survey, 1999, U.S. Census Bureau, Department of Commerce.

[2] The weight placed on the exceptional distribution is done here to make the example clearer. It is useful to note that the Practice-based entrepreneur's distributional prior can be very close to the Theory-based entrepreneur's prior for ordinary ideas; for example, when there is a very low prior probability held by the Theory-based entrepreneur that the idea is exceptional. Even such a relatively small change can lead to significant changes in potential observed search behaviour.

[3] One must solve for the value of x where is implicitly defined as $x = \int_x t dF(t) + \int^x x dF(t) - c$ given a distribution with cdf $F(t)$.

[4] Theory-based stopping rule calculated by finding the fixed point in the value function $v(z;\lambda) = \max\{z, \int v(\max\{z, x\}; \pi(\lambda, x)) dF(x;\lambda) - c\}$, where λ is the prior and $\pi(\lambda, t)$ updates that prior based on draw t. Contraction mapping code available upon request.

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