Programs of Experimentation and Pivoting for (Overconfident) Entrepreneurs

John S. Chen*
Warrington College of Business Administration, University of Florida
john.chen@warrington.ufl.edu

Daniel W. Elfenbein
Olin Business School, Washington University in St. Louis
elfenbein@wustl.edu

Hart E. Posen
School of Business, University of Wisconsin-Madison
hposen@wisc.edu

Ming zhu Wang
Olin Business School, Washington University in St. Louis
mingzhu@wustl.edu

June 2022

Forthcoming in *Academy of Management Review*

ABSTRACT: We develop a computational simulation to examine what we call the *program of experimentation* — a sequentially interdependent set of experiments and pivot decisions undertaken as an entrepreneur seeks to develop a viable business idea. We focus on two dimensions of the program design: the number of experiments to run and the pivot threshold for evaluating experimental outcomes. We address two critical issues. First, how much should an entrepreneur experiment and what are the implications for when to pivot? Second, how is the design of the program of experimentation conditioned by the nature of an entrepreneur's behavioral biases? Our computational model suggests that while experimenting and pivoting can improve new venture performance, it can also be taken too far. Programs of experimentation that generate frequent and early pivots may impede learning and underperform more conservative programs that generate fewer pivots. We also show that an effectively designed program of experiments can partially remedy entrepreneurs' behavioral bias. Overconfidence (specifically, over-estimation bias) favors a program design with a more aggressive pivot threshold, though this may not necessitate an increase in the number of experiments. Our work informs scholarly attempts to improve our understanding of the Lean Startup's strengths and limitations.

Keywords: entrepreneurship, learning, pivots, bias

* Authors listed in alphabetical order — all authors contributed equally. We thank seminar participants at Arizona State University, Baylor University, Bocconi University, Harvard Business School, Syracuse University, Washington University in St. Louis, University of Maryland, University of Nevada Las Vegas, University of Texas, and the London Business School Ghoshal Conference for their helpful comments, as well as Scott Cook, co-founder of Intuit, Christopher Pryor, and Alex Settles for useful conversations on the topic of the minimum viable product.

1. INTRODUCTION

The past two decades have seen a remarkable change in the conventional wisdom about entrepreneurship. For much of the twentieth century, a key to success for an entrepreneur was thought to be persistence. An entrepreneur should plan in advance and stay-the-course, because, as the saying goes, "quitters never win and winners never quit."[1] This narrative, and indeed, the normative advice, has changed. The advice is now to "fail fast and fail often," a mantra that, more recently, has been complemented by "pivoting your way to success."[2,3] This sea-change in conventional wisdom has its roots in the Lean Startup movement that has spread widely in Silicon Valley and beyond (Ries 2011, Blank 2013), and the term "pivot" now pervades the popular business lexicon. Effort to construct a theoretical foundation for elements of the Lean Startup is much needed, although such effort is still nascent.

There is growing scholarly interest in understanding *experimenting* and *pivoting* as integral to a scientific approach to venturing (e.g., Contigiani and Levinthal, 2019; Shepherd and Gruber, 2021), although the literature has yet to fully articulate the conceptual logic underlying how much to experiment and its implications for how often to pivot. Research has highlighted the benefits (e.g., Eesley and Wu, 2020; Felin, Gambardella, Stern, and Zenger, 2020; Bocken and Snihur, 2020), and somewhat less frequently the costs and challenges (e.g., McDonald and Gao, 2019; Hampel, Tracy and Weber, 2020) of experimenting and pivoting. Yet, as Ries (2011: p.8) recognizes, "there is often a misconception that it [the Lean Startup] offers a rigid clinical formula for making pivot or persevere decisions. This is not true."

We seek to develop design principles underlying what we call a *program of experimentation* — a sequentially interdependent set of experiments and pivots undertaken as an entrepreneur seeks to develop a viable business idea. In our view, the "program" is a critical unit of

[1] This conception is exemplified by entrepreneurs like Richard James, the inventor of the Slinky. The firm, James Industries, was on the verge of failure due to little market excitement and sales. The Slinky was a "pure dud." Until, that is, an innovative display of the product in Gimbels Department Store, turned the product into a huge success. https://www.inc.com/jeff-haden/the-couple-who-sold-300-million-toys-reveal-a-brutal-truth-about-success.html

[2] https://www.forbes.com/sites/groupthink/2014/09/19/the-right-way-to-launch-a-successful-new-product/#647fa7d65453

[3] https://globalman.co/adam-markel-pivot-way-success/ [accessed 6/29/2020]

entrepreneurial decision-making. A growing and active body of research has focused on individual experiments or the individuals' capacity to experiment effectively (e.g., Camuffo, Cordova, Gambardella and Spina, 2020; Leatherbee and Katila, 2020; Kirtley and O'Mahony, 2020; Grimes, 2018; Contigiani, and Young-Hyman, 2021). Rather than thinking about outcomes related to one specific experiment in isolation, a program's design goal is to develop a set of experiments that lead to a successful startup, independent of the outcome of any given experiment. Thus, our focus is not on the question of whether or under what conditions experimenting and pivoting is good or bad, but rather, how the program should be designed.

We focus on two choices that an entrepreneur makes about rules to follow when designing a program of experimentation when resource constraints limit the time available for doing so. The first choice is the number of experiments to conduct. This choice is necessary because new experiments are not costless, and resources, in terms of dollars, attention, and time, are constrained. Given this constraint, the entrepreneur faces a tradeoff of running more, shorter experiments, or fewer, longer ones. The second choice is the pivot rule in terms of the performance threshold for determining whether to pivot or not. A firm should pivot when the experimental test "rejects the business model hypothesis" (Eisenmann, Ries, and Dillard 2013, p.10). However, the appropriate threshold for determining experimental success or failure is ambiguous when feedback is noisy and subject to uncertainty.

We argue that the effectiveness of a program of experimentation is strongly impacted by the nature of entrepreneurs' behavioral biases. The design of a program, then, should not simply be a one-size-fits-all function of the economic and technical challenges facing the venture. The entrepreneurship literature, over the past few decades, has highlighted individual behavioral bias in decision making, confidence biases in particular, as a primary driver of mistakes made by entrepreneurs such as delayed exit and excess entry (Cooper, Woo, and Dunkelberg, 1988; Busenitz and Barney, 1997, Camerer and Lovallo, 1999). We demonstrate how the appropriate design of the program of experimentation changes when entrepreneurs exhibit combinations of two types of confidence biases: over/under-estimation bias and over/under-precision bias (Moore and Healy 2008).

To develop a deeper understanding of the design of a program of experimentation, and provide new insights into the relationship between experimenting and pivoting, we develop theory via a computational model that builds on the entrepreneurial learning model of Chen et al. (2018). Our model makes a number of noteworthy predictions.

First, a well designed program of experimentation should be premised on conducting a moderate number of experiments and using a balanced (i.e., not overly aggressive) pivot threshold. The Lean Startup approach, like other approaches to learning, is bounded by the challenges of acquiring and making use of new information. Excessive experimentation, particularly when coupled with an aggressive pivot threshold, limits learning within any particular experiment and leads to erroneous market entry decisions. A critical implication of the model is that the choice of the pivot threshold is strongly dependent on the choice of the number of experiments. Thus, a pivot threshold set for an experiment in isolation, without consideration of the broader program of experimentation, may produce outcomes that are far from optimal.

Second, the design of programs of experimentation must adapt in response to entrepreneurs' behavioral biases. An entrepreneur with over-estimation bias, for example, should evaluate experiments on the basis of a more aggressive pivot threshold than an unbiased entrepreneur, while committing to a similar number of experiments. Likewise, if entrepreneurs are employing an aggressive pivot threshold, then an over-estimating entrepreneur should commit to conducting more experiments than an unbiased entrepreneur.

Third, from an empirical perspective, our model predicts a negative correlation between the count of pivots undertaken by the observable (to the econometrician) set of entrants and new venture performance. Entrepreneurs' choices in the design of their programs of experimentation will typically not be observable by empirical researchers, yet, as our model shows, they critically influence behavior and performance post entry/scale-up. This occurs because the number of pivots is not the choice variable itself, but rather the result of program design (i.e., choice of the number of experiments and pivot threshold) — and pivots occur when an experiment is believed to have failed. Thus, observing such a correlation in the data of a set of entrants does not necessarily imply that the Lean Startup approach is flawed, but rather, that it is functioning effectively.

The outcomes of our model also shed light on some of the basic prescriptions promoted in the practitioner literature. Most notably, our model calls into question the universality of the popular wisdom that entrepreneurs should "pivot early and often." Building in opportunities to pivot creates value for entrepreneurs, as the Lean Startup suggests, but only as long as entrepreneurs refrain from conducting too many short experiments *and* choosing pivot thresholds that are too aggressive — choices that interact together in a way that blocks effective pre-entry learning. In addition, our model suggests that pivoting may be a remedy for bias, an idea suggested by Eisenmann, Ries, and Dillard (2013). As overconfidence problems become more severe, entrepreneurs benefit from choosing more aggressive pivot strategies, i.e., raising their pivot thresholds. More generally, a well designed program of experimentation can substantially improve performance for overconfident entrepreneurs, compared to when they commit to evaluating a single idea.

We proceed as follows. We begin with a theoretical background that draws connections to research on entrepreneurial experimentation, learning, and bias that inform the structure of our model. In section 3, we outline the computational model. We exercise the model in section 4, and conclude with a discussion of implications and limitations.

2. THEORETICAL BACKGROUND

Scholars have long recognized that entrepreneurship is a process of learning under uncertainty (Woo, Daellenbach, and Nicholls-Nixon, 1994; Minniti and Bygrave, 2001). Yet, as Cope (2005, p. 373) argues, "in terms of theory building, many aspects of entrepreneurial learning remain poorly understood." Recent theoretical research has begun to address this gap by focusing on learning as the critical mechanism underlying the process of new venture formation. For example, Chen *et al.* (2018) demonstrate that a simple learning model can account for many of the stylized facts highlighted in the empirical entrepreneurship literature, including excess entry, delayed exit, and a positive correlation between market entry cost and persistence with a failing idea. Empirical research has also directed its attention to entrepreneurship as a process of learning. For example, Bennett and Chatterji (2019) survey prospective entrepreneurs and find significant heterogeneity in approaches to pre-entry learning across respondents.

The Lean Startup is quite explicitly a learning approach to understanding entrepreneurship (Contigiani and Levinthal, 2019). The "build-measure-learn" idea at the center of Ries (2011), with the experimenting and pivoting it suggests, is a learning process. Below, we highlight the nature of learning in the Lean Startup, how it is related to learning as a more general theoretical construct, and the factors that make such learning challenging. We then consider how entrepreneurs' behavioral biases further complicate the learning process.

2.1 Entrepreneurial learning in the Lean Startup

Entrepreneurial learning, particularly in the sense of the Lean Startup, is related to but substantively different from broader ideas of organizational learning (e.g., Argote 1999). In our view, three interrelated factors underlie differences between learning in a general organizational sense and learning in an entrepreneurial sense of the Lean Startup.

First, experiments and pivots are fundamental ideas in the Lean Startup and underlie the basic elements of the learning, which plays out over time in a sequential cyclical manner. Experimentation denotes purposely designed small-scale, relatively cheap, market-based tests of important elements of the business idea (Murray and Tripsas 2004, Bingham and Davis 2012). A pivot is a "structured course correction designed to test a new fundamental hypothesis about the product, strategy, and engine of growth" (Ries, 2011: p.8). An entrepreneur pivots when feedback from an experiment "indicates that greater opportunity lies elsewhere" (Eisenmann, Ries, and Dillard 2012, p.10). Experiments and pivots are potentially quite costly, the former in terms of designing and conducting the experiment, and the latter because pivoting to a new idea entails overhead such as procuring assets for the new experiment, setting up a new schedule of activities, and the logistics of launching a new experiment.

Each experiment is a single "build-measure-learn" cycle in the sense of Ries (2011). The entrepreneur "builds" the minimum viable product (MVP), which is sufficiently-specified to gather information about the quality of the business model idea. She measures – that is, she conducts a market test to gather data on the idea. Then she learns – she updates her beliefs about the merits of the idea. At the end of this cycle, the entrepreneur makes the pivot decision in that she either persists with the current idea or pivots to a new idea variant for the next experiment.

Research has begun to study experimenting and pivoting. Felin, Gambardella, Stern, and Zenger (2020) and Bocken and Snihur (2020) debate the merits and implications of experimentation. Eesley and Wu (2020), consider how adaptability, an idea that is implicit in experimenting, impacts short and long run performance of new ventures. Research taking a sociological approach, building on Lounsbury and Glynn (2001), has examined the implications of pivoting for how audiences perceive a venture's ideas in terms of legitimacy (McDonald and Gao 2019) and stakeholders who identify with the venture (Hampel, Tracy and Weber 2020).

A core feature of the build-measure-learn concept is that it proceeds in a cyclical manner as experiments are conducted sequentially over time — and this is why we believe that consideration of the *program of experimentation* is so critical. As Kerr, Nanda, and Rhodes-Kropf (2014) suggest, the historical foundations of the Lean Startup rest on the idea that entrepreneurs engage in a "process of experimentation." McDonald and Eisenhardt (2020, p. 515) recognize this as a process of "continuous experiments and pivots." Thus, we must think about the Lean Startup as build-measure-learn-REPEAT. By undertaking a sequence of experiments and pivots, the entrepreneur can examine new and potentially successful ideas when previously tried ideas appear unpromising. While the design of any given experiment is certainly important, so too is the design of the broader program of experimentation in terms of clear choices as to the number of experiments that will be undertaken and the threshold for pivoting.

Second, the Lean Startup focuses on learning-by-experimenting rather than learning-by-doing, although in practice, the differences rest on a continuum. At one extreme, learning-by-doing, which is extensively studied in management (see Argote 1999), is the experiential learning that "occurs when, in the course of *engaging in productive activity*, problems are identified, experiments are performed as solutions are sought, and solutions are implemented" (Posen and Chen 2013, p. 1701 italics added). Here, doing is the primary objective, and learning is a byproduct. At the other extreme, learning-by-experimenting is different in that learning is not a byproduct of doing but rather the primary goal of the process in and of itself. Work on experimenting as a means of learning is not unique to the Lean Startup. Experimentation creates an option to abandon ideas that turn out to be bad (Manso 2016). Uncertainty, endemic to the entrepreneurial context, makes this option valuable. Work on organizational experimentation often focuses on R&D processes at established organizations to study issues that arise in coordinating parallel vs sequential search (e.g., Loch, Terwiesch, and Thomke 2001). Of course, experimenting and doing are not mutually exclusive. As Contigiani & Levinthal (2019: 552) argue, the firm develops and potentially sells the "simplest version of the proposed product that can gain traction with a set of possible customers and, as a result, generate informative feedback," suggesting that the primary role of the experiment in learning-by-experimenting is to learn rather than the maximize the value created for users.[4]

Third, entrepreneurial learning involves two phases: pre-entry and post-entry. The two phases are divided by the market entry decision associated with scaling up of activities to serve the larger market. During the pre-entry period, a firm learns but does not (substantially) earn. Experimentation may well take place in the market, engaging with customers and selling

[4] Learning by experimenting is not only an entrepreneurial phenomenon. Work on economic activity as a process of experimentation has a long history in the management and economics literature (Kerr, Nanda, Rhodes-Kropf 2014), whether or not those experiments happen within firms or across firms (e.g., Rosenberg 1994, Nelson and Winter 1982). For example, R&D departments of large firms might also engage in pre-entry experimentation followed by post-entry commercialization. Extending our theoretical exercise into a corporate setting is possible. Indeed, Ries (2017) extends the Lean Startup to established firms, as the differences between startups and incumbents exist not in a binary sense, but on a continuum.

relatively small volumes, such that feedback is informative. However, such experimentation only reaches a small part of the market, which keeps the test relatively cheap and limits downside risk. Much of the discussion in the Lean Startup is focused on this pre-entry phase. The pre- and post-entry phases are connected via the market entry and scale-up decision – a decision as to whether the venture should exit or scale-up to serve the larger market. Yet it is not just the go/no-go decision itself that is the critical distinction between the phases. Post-entry, the scale-up to serve the broader market involves a substantial increase in costs, in terms of both the sunk cost of entry and the risk of substantial operating losses. The post-entry period, then, is one of much higher commitment than the pre-entry period (Agrawal, Gans, and Stern 2021). For example, Spotify experimented with a small collection of songs to validate demand for music streaming in what we would refer to as the pre-entry (i.e., pre-scaling) period. Once sufficient learning took place to establish demand, Spotify fully entered the market, scaling their operations and music collection to serve a mass market.

2.2 Challenges of experimenting and pivoting

Scholars have begun to explore the many challenges inherent in experimenting and pivoting. One challenge surrounds questions of what and how much can be learned from an experiment. An entrepreneur spends the time to develop the MVP, conducts, and learns from feedback. One might imagine a "perfect MVP" – a prototype that produces the perfectly definitive answer to a hypothesis test. But such a view reflects an extreme simplification. There may be no perfect MVP in this sense. All experiments produce at best noisy signals – the question is the degree of noisiness. One hopes that the MVP (and the design of the experiment) leads to a high signal-to-noise ratio such that the experiment is informative.[5] Indeed, the mantra of "cheap" experimentation must come at some cost, notably, less-than-perfect MVPs and smaller scale data collection, which makes learning from the noisy signal challenging. Felin, Gambardella, Stern,

[5] Recent theoretical work examines the informativeness of experimentation as one of the key drivers of whether firms should adopt a Lean Startup approach (see Shelef, Wuebker, and Barney 2020 and Contigiani 2020).

and Zenger (2020, p.1) argue that the Lean Startup with its "emphasis on readily observable feedback and immediately validated learning" under-estimates the challenge of learning from feedback. Agarwal et al. (2020) recognize that "any single test conflates the signal of the efficacy of the particular strategy and the quality of the idea" and thus, they generate very "noisy estimates of the value of an idea" (Gans, Stern, and Wu 2019: p.744). In the management literature, these challenges are well-known (e.g., Levinthal and March 1993). Data may be sparse, as March, Sproull, and Tamuz (1991) note; choices may involve selection over alternatives that are themselves evolving (Levinthal and Posen 2007); and the choice of what to sample is endogenous (Denrell and March 2001).

These challenges are exacerbated because entrepreneurs may not be good experimental designers. Camuffo, Cordova, Gambardella and Spina (2020) use a field experiment to examine how training in a scientific approach to experimentation, forming and falsifying hypotheses, impacts performance. Those trained in a scientific approach were more likely to pivot and more likely to choose not to enter. In a sample of NSF-supported lean-startup teams, Leatherbee and Katila (2020) find that reluctance to embrace the experimentation methodology, due to training in "learning-by-thinking," undermines performance. Kirtley and O'Mahony (2020) study seven entrepreneurial firms closely and conclude that pivots occurred only when new information was in conflict with the entrepreneurs' prior beliefs. Grimes (2018) finds that collective sensemaking makes entrepreneurs more open to performance feedback. Contigiani and Young-Hyman (2021) find that formal structure interacts with the efficacy of learning by experimenting.

Entrepreneurs also face the challenges inherent in balancing exploitation of known ideas and exploration of new, but not well understood ideas. Learning requires resources, specifically money and time, that are almost always scarce for entrepreneurs. Given this scarcity, there will be an inherent trade-off between exploration and exploitation (Holland 1975, March 1991, Posen and Levinthal 2012). As Gans et al. (2019, p. 738) note, "entrepreneurs using experimentation to gauge whether or not to proceed...run the risk of incurring significant opportunity costs from the process of experimentation itself, potentially foreclosing them from other strategic alternatives." The literature on learning, building on the behavioral theory of the firm (Cyert and March 1963), argues that firms and individuals exhibit a tendency toward exploitation.

Opportunities for experimentation and learning are shaped not only by the availability of resources, but also by the characteristics of the environment itself. Foss, Klein, and Bjornskov (2019) emphasize this connection: "the market or task environment determines the need for experimentation (e.g., how fast do consumer preferences change, how does technology evolve, which assets are available at which terms, etc.)." Nanda and Rhodes-Kropf (2016) focus on the costs of experimentation, and argue that falling costs, especially in computing, have dramatically changed the landscape of entrepreneurship itself. A related line of inquiry argues that data availability affects the construction of precise target groups for whom highly-discriminating tests can be designed (Bland and Osterwalder 2019). Yet even where more experimenting and more aggressive pivoting is warranted by the environment, resource constraints may hinder the entrepreneur's ability to proceed with experimenting at the desired rates.

A different set of challenges is recognized in the sociological literature on entrepreneurship. Entrepreneurs may face multiple distinct audiences, such as funders, customers, and suppliers. Research has considered how ideas are shaped, improved, or legitimized as entrepreneurs expose ideas to these different audiences (Wry, Lounsbury, and Glynn 2011; Lounsbury and Glynn 2019). Different audiences may provide very different feedback when an experiment is conducted, or they may differentially make sense of the results of any given experiment. These different audiences may interact with the entrepreneur's own identity to shape sensemaking and feedback (Navis and Glynn 2011). In this sense, the quality of the idea may be, in part, socially constructed, and the process by which entrepreneurs come to change their ideas is not independent of its audiences and their reactions.[6]

2.3 Behavioral bias

The challenges inherent in learning from experimentation may be further complicated by the cognitive biases of entrepreneurs themselves. One cannot consider the efficacy of the Lean Startup without considering entrepreneurs willingness and ability to learn, the most salient determinant of which are cognitive biases. Eisenmann, Ries, and Dillard (2013) raise the possibility that the Lean Startup approach may be a remedy for entrepreneurs' behavioral bias. Yet it is not clear, *ex ante*, whether or how the Lean Startup approach functions to potentially mitigate bias, or the types of bias for which it is effective. Moreover, it is not clear how a program of experimentation should change in order to mitigate bias.

Overconfidence has become an almost taken-for-granted characteristic of entrepreneurs, and scholarly work only reinforces this view. Cooper, Woo, and Dunkelberg (1988) survey 3000 entrepreneurs and find many of them hold far higher beliefs that they will succeed in comparison to their belief that others will succeed. Similarly, Busenitz and Barney (1997: 10) find that, with respect to overconfidence, entrepreneurs "behave differently than do managers in large organizations and … these differences are substantial." Related research has examined many other implications of overconfidence for entrepreneurial decision-making and performance (e.g., Camerer and Lovallo 1999, Hayward, Shepherd, and Griffin 2006, Lowe and Ziedonis 2006, Dushnitsky 2010, Sandri, Schade, Musshoff, and Odening 2010, Cain, Moore, and Haran 2015, Gutierrez, Åstebro, and Obloj 2020).

Scholars in psychology have recently observed that confidence biases manifest in multiple ways, each of which has different implications for learning. The literature distinguishes between

[6]As Hampel, Tracy and Weber (2020: p.440) argue, the act of pivoting itself, "risks disrupting relationships with key stakeholders, such as user communities, who identify with ventures," thus changing to a new idea may make subsequent experiments more challenging to interpret. McDonald and Gao (2019: p.1289) recognize that entrepreneurs must "anticipate, justify, and stage changes to various audiences." Moreover, these processes may undermine the willingness to pivot because, as Grimes (2018: p.1692) argues, entrepreneurs "may view aspects of their creative ideas as linked to their self-concepts, this can trigger resistance toward revision." This research suggests that entrepreneurs frequently receive feedback that is neither impartial nor unequivocal, reducing the signal-to-noise ratio and making learning via experimentation challenging.

over-estimation, indicating that an entrepreneur thinks that her idea is better than it is, and over-precision, where an entrepreneur holds to her beliefs too strongly (i.e., does not update her beliefs enough) when confronted with new information (Moore and Healy 2008).[7]

Over-estimation and over-precision have clear applications to entrepreneurial learning. Over-estimation occurs when entrepreneurs believe an opportunity to be better than it actually is at the outset, thereby starting the learning process with overly optimistic prospects for its success. Thus, over-estimation makes it more likely for an entrepreneur to enter and persist in the market. Over-precision occurs when an entrepreneur is too certain about (i.e., has too small of a confidence interval around) her estimate of the success prospects of the opportunity. In the extreme, a highly over-precise entrepreneur completely ignores new information. Over-precision has been shown, through formal models, to have important implications for learning and performance in entrepreneurial ventures (Posen, Leiblein, and Chen 2018, Chen *et al.* 2018, Chen, Elfenbein, Posen and Wang 2022).

2.4 Implications

Taken together, this suggests the following caricature of entrepreneurship in the Lean Startup sense that—although abstracting away from many details in Ries (2011)—captures the essential logic of the process behind a *program of experimentation*. Our focus is on an entrepreneur who utilizes a fixed amount of time, corresponding to what practitioners often call the "entrepreneurial runway," to study ideas of uncertain quality, sequentially, prior to the high-commitment scale-up decision associated with full market entry. She begins with an initial idea and decides on the features of her *program of experimentation*—the *number of experiments* which, given fixed resources, determine their length, and the *pivot threshold* in terms of the performance outcome from experiments below which she will pivot to a revised idea. She conducts the first experiment with the initial idea—building an MVP, measuring performance,

[7] Moore and Healy (2008) also identify a third type of confidence bias, overplacement, where an entrepreneur views herself too favorably compared to others.

and updating her beliefs about its merits. Because the new information the entrepreneur receives is noisy, corresponding to the highly varied feedback that entrepreneurs receive from potential customers, suppliers, and advisors in practice, her beliefs at any point in time represent an incomplete understanding of the idea's merits. Nonetheless, a pivot decision must be made. The entrepreneur compares these updated beliefs to her pivot threshold. If they are below the threshold, then she pivots to a revised (i.e., next) idea and repeats the cycle, otherwise, she may conduct another experiment designed to gather more data on the current idea. When resources are exhausted and the set of experiments conclude, she decides whether the best idea is sufficiently good to enter the market. Should the entrepreneur choose to enter, she continues to learn about the quality of the chosen idea, and because not all ideas generate positive profits, she may subsequently choose to exit.

3. COMPUTATIONAL MODEL

We conceptualize entrepreneurship as an unfolding feedback-learning process through which an entrepreneur discovers the viability of their opportunities and makes market entry and exit decisions. We begin with the baseline model (i.e., with neither experimenting nor pivoting) in which a prospective entrepreneur engages with a single idea in a process of pre- and post-entry learning. Learning starts pre-entry, when the entrepreneur learns but does not earn. Conditional on a positive entry decision, the entrepreneur continues to learn but accumulates profits and losses, and may choose to exit at any time if it comes to believe the venture is unprofitable. We then extend the model to enable the prospective entrepreneur to sequentially experiment in the pre-entry period. The entrepreneur starts with an initial idea, if the experiment shows promise, she persists with it to conduct (potentially) another experiment, otherwise she pivots to a new idea. The entrepreneurs in our simulation make market entry and exit decisions that maximize profits conditional on their beliefs, which may or may not be accurate due to bias. Our interest is in examining the effective design of a program of experimentation in terms of the number of experiments to run and the pivot threshold. Table 1 summarizes the main assumptions and mechanisms of the model, and previews the key outcomes in our simulations.

<INSERT TABLE 1 HERE>

3.1 Baseline model without experimentation

In this section, we summarize the model of Chen, Croson, Elfenbein, and Posen (2018), henceforth CCEP, from which forms our baseline (no experiments or pivots) model. CCEP augments Ryan and Lippman's (2003) model of exit from a project with uncertain returns by adding pre-entry learning and behavioral bias. The pre-entry period in CCEP, which has a fixed duration Λ, is used by the entrepreneur to evaluate an idea. For example, the entrepreneur might conduct market research, investigate potential partnerships, or engage in prototyping efforts. For simplicity, we assume pre-entry activities are costless to the entrepreneur. If, at the end of the pre-entry learning period, the entrepreneur believes the venture to be sufficiently likely to succeed, she will pay a cost k to conduct a full-scale market entry. After entry, entrepreneurs accrue profits and losses, which also serve to update their beliefs on the quality of the idea and may lead to exit if beliefs become sufficiently low.

CCEP considers two types of business ideas: type-H, or a "good" idea, with profit rate $\mu = \mu_H > 0$, and type-L, or a "bad" idea, with profit rate $\mu = \mu_L < 0$. An idea is type-H with probability p and type-L with probability $1 - p$; in both cases profit variance across pre- and post-entry periods is σ^2.[8] Post-entry profits are discounted at a rate $\delta > 0$, and cumulative profits follow a Brownian motion with drift μ and variance σ^2.

The entrepreneur does not know *ex ante* whether an idea is good or bad (i.e., μ is unknown) but knows the other Brownian motion parameters and p. The variable $\hat{p}_t$ denotes an entrepreneur's belief about the probability that an idea is type-H at time t, which evolves with the noisy profit signals the entrepreneur receives. At the beginning of the pre-entry period (i.e.,

[8] The model is easily modifiable to allow for different noise parameters pre- and post- entry. See CCEP (2018) for a discussion.

$t = -\Lambda$), a rational entrepreneur's belief that the idea is type-H is $\hat{p}_{-\Lambda} = p$. For a type-H (type-L) idea, $\hat{p}_t \to 1$ ($\hat{p}_t \to 0$) as $t \to \infty$, i.e., with enough time entrepreneurs learn about the quality of the idea with certainty. Details on the process of belief updating are provided in Appendix A.

An entrepreneur enters if her expected returns exceed the entry cost k. Given that there is a monotonic relationship between $\hat{p}_0$, the entrepreneur's belief about the probability of a type-H idea at $t = 0$, and expected returns, the entrepreneur enters if $\hat{p}_0$ is above a threshold that is a function of k.[9] Post entry, the decision to exit is an optimal stopping problem. The entrepreneur exits the market at time t if its belief on being a high type, $\hat{p}_t$, falls below a threshold p^*.[10]

3.2 Model with a program of experimentation in the pre-entry period

We extend the model described above to allow for a program of experimentation in the pre-entry period in which the entrepreneur sequentially conducts experiments and evaluates whether to pivot across ideas. The model is, of course, a simplification of the build-measure-learn cycle popularized by the Lean Startup movement, but one that seeks to "accurately capture some salient aspects of some phenomenon... while still being parsimonious" (Makadok, Burton, and Barney 2018: p.1531). The entrepreneur's behavior during this pre-entry period is a function of the specifics of her program of experimentation in terms of the number of experiments and the pivot threshold. At the end of the pre-entry period, the entrepreneur enters with the most promising idea she believes she encountered if and only if she believes it will deliver expected profits that exceed the entry cost k.

We denote the ideas evaluated during the pre-entry period as I_1, I_2, I_3, …, where I_1 is the idea with which the entrepreneur begins the pre-entry learning period. We define X as the total number of experiments in the program, and let x_1, x_2, ..., x_X denote each of the experiments.

[9] In our analysis, we utilize Ryan and Lippman's closed-form expressions for an entrepreneur's beliefs and expected return at time t, both of which are a function of p and the Brownian motion parameters.

[10] An expression for p^* in terms of model parameters is given by equation (7) of Ryan and Lippman (2003: 442). Given the parameters we choose in our model, the value of p* for unbiased agents is 0.1273.

When $X = 1$, the entrepreneur learns about a single idea for the entire pre-entry period with no opportunities to pivot. Since the pre-entry learning period, Λ, is fixed due to resource constraints, increasing X means running shorter experiments. At the end of each experiment, the entrepreneur conducts an assessment, in which all existing information about idea I_j is examined. The entrepreneur's decision to continue with I_j or pivot to idea I_{j+1} is taken by comparing its belief that the idea is type-H to the pivot threshold θ. Each time the entrepreneur switches to a new idea, we count a pivot, and we define the total number of pivots as N.

We incorporate into the model two types of process-related costs associated with experimentation, both of which consume time rather than financial resources. First, assessing the results of an experiment—data cleaning, analysis, and decision-making—cannot be done entirely in parallel and takes time that otherwise could be devoted to learning. We denote this assessment time-cost κ_a, which is deducted from the end of each experimentation period. Second, pivoting to a new idea entails overhead such as procuring assets for a new MVP, setting up a new schedule of activities, and the logistics of launching a new experiment. We label these time costs κ_p, and assume they are only incurred when the entrepreneur decides to pivot.[11] Figure 1 sketches the model timing for a program of $X = 4$ experiments (assuming $\kappa_a = \kappa_p = 0$) with an example time series of how beliefs about each idea might evolve and the consequences for decision-making.

<INSERT FIGURE 1 HERE>

The model contains a number of assumptions about learning. First, we assume that the entrepreneur can only experiment sequentially, on one idea at a time. Following the Lean Startup literature, we think of experiment x_k as containing an entire "build-measure-learn" cycle that generates data about the quality of a single business idea, I_j.[12] At the end of this cycle, the

[11] This pivot cost is distributed equally among all future experiments. For example, if the firm pivots after experiment g, then its learning time in all subsequent experiments is reduced by p/(X-g).

[12] We conceptualize an idea as a "business model" in the sense that it contains a set of answers to the questions posed by the business model canvas (BMC) or scholars like David Collis who collapse BMC questions into choices about objectives, proposed advantage, and business scope (Collis 2010). Here scope encompasses multiple dimensions, including which customers to target and with what offering, geographic location, and vertical integration. We recognize that ideas have subcomponents, and that I_j and I_{j+1} may differ on one subcomponent or on many. By assumption, however, ideas I_j and I_{j+1} are "different enough" that it costs κ_p to switch.

entrepreneur can choose to direct x_{k+1} toward learning more about I_j, or she can pivot and direct x_{k+1} toward learning about a new idea, I_{j+1}. In this sense, ideas are independent, insofar as any experiment only provides information about a single idea. Second, we assume that the entrepreneur retains what she has learned in all prior experiments and may choose any idea she has studied to enter the market. Finally, for the sake of mathematical simplicity, we assume that once the entrepreneur has switched from I_j to I_{j+1}, she cannot conduct any additional experiments with an old idea (I_j, I_{j-1}, etc.).

3.3 Incorporating confidence bias

We incorporate two types of confidence-related behavioral biases, following the modeling in CCEP, which builds on Moore and Healy (2008). First, entrepreneurs may have biased initial beliefs and exhibit *estimation bias*. We designate the initial beliefs about the probability that I_j is high-type as $\hat{p}^{init}$. Values of $\hat{p}^{init} > p$ reflect over-estimation (optimism), while $\hat{p}^{init} < p$ reflects under-estimation (pessimism).[13] Second, entrepreneurs may have biased beliefs about the noisiness of profit signals and exhibit *precision bias*, where precision τ is, per standard convention, defined as the inverse variance in profit signals (*i.e.*, $\tau = 1/\sigma^2$). τ determines the optimal rate of belief updating given new information from an experiment. If τ is low, then the new information is very noisy, and the entrepreneurs beliefs should rationally change very little. We use $\hat{\tau}$ to denote the entrepreneur's assessment on τ. $\hat{\tau}/\tau < 1$ reflects *over-precision* in that entrepreneurs update beliefs too slowly (relative to a Bayesian learner) because they assume profit signals to be less informative than they really are. Conversely, $\hat{\tau}/\tau > 1$ reflects *under-precision* in that entrepreneurs update beliefs too rapidly because they assume profit signals to be more informative than they really are.

[13] The literature, in some cases, specifies over-estimation as a bias in some specific task while optimism is a trait-like property of individuals. Our model is agnostic between the two ideas. That is, an entrepreneur that is biased in this way will initially over-estimate all of her ideas equally. In this sense, while we can think of it as specific to the task, we can also think about it as a trait-like characteristic of the entrepreneur.

3.4 Program of experimentation rules, simulation parameters, and output

Programs of experimentation in our stylized model, as noted earlier, consist of two choice rules. The first rule is the number of experiments, X, to run. We consider situations ranging from $X = 1$ to 20 experiments. Note that running 20 experiments does not mean engaging in 20 pivots. If an experiment points to the success of the idea, the firm may experiment with that same idea again to gain additional data to ensure that the idea is, in fact, a profitable one.

The second rule is the pivot threshold. This rule takes the form of a threshold for beliefs, θ, above which the entrepreneur sticks with learning about I_j and below which the entrepreneur pivots to learning about I_{j+1}. The entrepreneur proceeds from I_j to I_{j+1} if her belief is $\Pr(I_j =$ type-H$) < \theta$. We consider three main settings. First, we define a *balanced threshold,* $\theta = 0.5$*,* which we consider a natural baseline assumption. With this threshold, the entrepreneur proceeds from I_j to I_{j+1} if her belief is $\Pr(I_j =$ type-H$) < 0.5$. That is, the unbiased entrepreneur pivots if and only if the new idea has a greater *ex ante* chance of success than the existing one. Second, we define a *conservative threshold* as $\theta = 0.45$. Observed pivots for this threshold are thus less common than for the balanced threshold. Finally, we define an *aggressive threshold*, $\theta = 0.55$. This threshold represents the desire by the entrepreneur to "stick with winners." If the idea is not clearly better than the pool of alternatives, the entrepreneur pivots to study a new idea.

We focus primarily on the expected value of new venture profits conditional on the entrepreneur's program of experimentation and potential bias. Given that σ, μ_H, μ_L and δ are fixed, performance is determined by entry cost (k) and incidence of three types of errors: (1) *mistaken entry*, in which the entrepreneur enters with a type-L idea, (2) *mistaken non-entry*, in which the entrepreneur fails to enter despite having encountered a type-H idea during the pre-entry period, and (3) *mistaken exit*, in which the entrepreneur enters with a type-H idea but subsequently leaves the market. The cost of mistaken entry increases in k, and also in *exit delay*, which results from the entrepreneurs' pivot strategies. In all simulations, each idea has a 50% chance of being type-H, and we set parameters to $\mu_L = -50$, $\mu_H = 50$, $\sigma = 100$, and

$\delta = 0.1$. In our main simulations we set $\Lambda = 1$ and the entry cost, k, equal to 153.7, which makes an entrepreneur indifferent between launching an idea that she believes has a 0.5 likelihood of being type-H and not entering the market. This assumption ensures that the entrepreneur will not arrive at the end of a period and wish to enter with an entirely new (i.e., not previously studied) idea.[14] Additionally, we set $\kappa_a = 0.01$ and $\kappa_p = 0.05$.

4. SIMULATION RESULTS

In this section we report the impact of different programs of experimentation on the expected profits, entry, and exit behavior of entrepreneurs in our computational model. We focus initially in section 4.1 on unbiased entrepreneurs, detailing the underlying mechanisms that generate performance differences. In section 4.2, we consider entrepreneurs with bias, where our focus is on identifying the program of experimentation that best addresses the bias. In section 4.3, we examine the implications of our model for empirical studies that seek to link observed pivots to performance. We conclude in section 4.4 by relaxing the assumption that distinct experiments have equal length, to explore whether entrepreneurs will benefit from strategies that can lead to *early pivots*. We explore the robustness of our analyses to a wide range of alternative parameters, k, Λ, κ_a, and κ_p in the Online Appendix.[15]

4.1 Program of experimentation when entrepreneurs are unbiased

We seek to understand the basic features of the design of a program of experimentation for unbiased entrepreneurs. We vary the number of experiments, X, in the pre-entry period from 1 to 20, where $X = 1$ is the case in which the entrepreneur commits to spending the pre-entry period investigating a single idea (i.e., a 'no-pivot' policy). We examine how the pivot threshold (*conservative*, *balanced*, or *aggressive*) interacts with an entrepreneur's choice about the number

[14] Lower values of k reflect entrepreneurial environments that are more favorable, in the sense that the expected value of entry for rational agents with no pre-entry information is greater than the entry cost. Higher values of k reflect environments in which uninformed, but rational, entrants fail to earn their entry cost in expectation. Higher values of k might be thought of as consistent with the entrepreneurial environment explored by Hamilton (2000), in which the median entrepreneur fails to earn what she would have earned had she remained in paid employment.
[15] Online Appendix is available at [INSERT URL].

of experiments to affect entry decisions and expected profitability. Figure 2 plots the expected profitability and average number of pivots taken as a function of the number of experiments and the pivot threshold chosen by unbiased entrepreneurs.

<INSERT FIGURE 2 ABOUT HERE>

One outcome in particular stands out — over a broad range of choices with respect to the number of experiments, *balanced* or *conservative* pivot thresholds dominate the *aggressive* threshold. As X increases, the disadvantage of the *aggressive* threshold increases, as it leads to too many pivots. A clear implication is that plans to run many experiments should be matched with more conservative pivot thresholds. More generally, a program of experimentation must be designed by considering the joint impact of the number of experiments and the pivot threshold.

Several additional features are noteworthy. Consistent with the intuition produced by the Lean Startup literature, moving from an exclusive focus on evaluating a single idea to a process where the entrepreneur has the opportunity to evaluate multiple ideas generates significant value. Under our main set of parameters, unbiased entrepreneurs have expected profits of 61.3 when committing to experiment with a single idea. Raising X from 1 to 2, and hence creating an option to experiment with a second idea, increases profits by roughly 18%, independent of the chosen threshold. Expected value continues to increase across each threshold as X increases further from 2 to 4, with improvements over the no-pivot approach of 28.7%, 32.8%, and 30.1% for *aggressive*, *balanced*, and *conservative* thresholds, respectively.

Unsurprisingly, for each pivot threshold, more experiments translate into more actual pivots. For $X = 10$, the conservative pivot threshold yields about 1.2 pivots on average (meaning that the entrepreneur explores 2.2 ideas), whereas the respective figures for balance and conservative thresholds are 2.4 and 4.2, respectively (3.4 ideas and 5.2 ideas). Exploring more ideas—the result of frequent pivots—does not necessarily lead to better performance, as the declining red and yellow lines on the left panel indicate. Thus, the model supports the Lean Startup principle pivot rather than commit, but it also suggests that too much pivoting, due to a design that features too many experiments or too aggressive pivot threshold may undermine this conclusion.

What drives these performance differences across programs of experimentation? The relative performance of the different programs of experimentation we examine does not simply result from the number of pivots they engender. Rather, their relative performance can be traced to the frequency and severity of errors they induce. As demonstrated in the right panel of Figure 2 (and in Online Appendix Figure C1), each program produces a different empirical distribution of actual pivots that, in turn, shapes the amount of performance information used to assess each idea, and hence affects the proportion of mistaken entry (entry with a Type-L idea), mistaken non-entry (decision not to enter despite having a type-H idea), and mistaken exit (entering with a type-H idea and subsequently exiting), as well as the exit delay (amount of time spent by type-L entrants in the market). Figure 3 plots the relative incidence of each error as a function of pivot threshold and number of evaluation opportunities.

<INSERT FIGURE 3 ABOUT HERE>

We focus our discussion of the figures on high values of X, i.e., on the right hand side of each graph. While the *balanced* and *conservative* thresholds generate significantly less entry than *aggressive*, they outperform the *aggressive* threshold at large X by generating fewer entry mistakes. As Figure 3 Panel A shows, at large X over 40% of entrepreneurs pursuing the *aggressive* threshold enter with type-L ideas. These entrepreneurs pay the entry cost k and also suffer losses while in the marketplace. By contrast, about 28% of *conservative*-threshold entrepreneurs mistakenly enter with type-L ideas. This large advantage compensates for the fact that slightly more than 9% of *conservative* entrepreneurs fail to enter with type-H ideas (Figure 3 panel B). Furthermore, *balanced, conservative,* and *aggressive* thresholds produce a very similar post-entry exit delay for type-L entrants (Figure 3 panel C), defined as the time a mistaken entrant requires to recognize the error and exit the market. However, the higher proportion of type-L entry fostered by the *aggressive* threshold generates total operating losses that are greater.

Finally, the *aggressive* pivot threshold produces a significantly higher incidence of type-H exit post-entry than the *balanced* or *conservative* thresholds (see Figure 3 panel D). Taken together, the panels in Figure 3 show that the *aggressive* approach generates inferior returns for unbiased entrepreneurs because it produces more mistaken entry, which incurs both significant entry costs and operating losses, as well as more mistaken exit; at $X = 20$, this more than compensates for its advantage in reducing mistaken non-entry.

In sum, the outcomes for unbiased entrepreneurs highlight the importance of considering a program of experimentation holistically. Underlying the design of an effective program of experimentation is the tradeoff between the number of experiments run and the criteria for evaluating the results of experiments to make pivot decisions. Given a fixed entrepreneurial runway, the more distinct experiments an entrepreneur plans to run, the shorter, and less informative, these experiments must become. In turn, this changes how cautious the venture should be in setting its pivot threshold to evaluate and act on the market feedback to make pivoting decisions.

4.2 Experimentation by biased entrepreneurs

We next examine the effectiveness of different programs of experimentation when entrepreneurs are biased. This enables us both to shed light on how the design of a program of experimentation must change to "treat" particular biases and to investigate the claim that Lean Startup prescriptions can *remedy bias* (Eisenmann, Ries, and Dillard, 2013). One key result, which we highlight below, is that over-estimation biased entrepreneurs should evaluate experiments on the basis of a more aggressive pivot threshold, and by doing so, will not necessitate an increase in the number of experiments.

4.2.1 Performance of overconfident entrepreneurs as a function of pivot threshold

We focus on two types of confidence bias that are known, both theoretically and empirically, to impede entrepreneurial decision-making, namely *estimation* bias and *precision* bias (Camerer and Lovallo 1999, Elfenbein, Knott, and Croson 2017). We begin by replicating the analysis above for entrepreneurs who exhibit *over-estimation* bias by itself, and for those who exhibit both *over-estimation* and *over-precision* bias together, a combination that has been shown to be particularly toxic in prior work (Chen *et al.* 2018). We model *over-estimation* as initial beliefs about $\Pr(I_j = \text{type-H})$ that equal 0.60, and *over-precision* bias as $\hat{\tau}/\tau$ equal to 0.5, meaning that entrepreneurs incorporate performance information less in updating their beliefs than would a Bayesian learner.[16]

Figure 4 replicates the left hand side of Figure 2 for these two types of overconfident entrepreneurs. In panel A, which explores *over-estimation* bias alone, committing to a single idea generates an expected value of 55.8, which is 8.9% lower than value created by a never-pivoting unbiased entrepreneur. Panel B, which examines entrepreneurs with both *over-estimation* and *over-precision* bias, committing to a single idea generates an expected value of 45.1.

<INSERT FIGURE 4 ABOUT HERE>

For overconfident entrepreneurs, the relative performance of programs of experimentation with *aggressive, balanced,* and *conservative* pivot thresholds differs dramatically when compared to unbiased entrepreneurs. For unbiased entrepreneurs, the *aggressive* threshold is never the best of the three policies for any choice of the number of experiments, *X*. By contrast, for our overconfident entrepreneurs, the *aggressive* threshold is always the best of the three policies. In fact, for the most overconfident entrepreneurs, namely those in panel B, *balanced* and *conservative* thresholds may yield little performance improvement when compared to "no pivots" and may even destroy value. Indeed the relative performance improvement offered by the *aggressive* threshold seems significantly higher for this combination of biases.

Figure 5 explores the reasons why *aggressive* outperforms *balanced* and *conservative* for entrepreneurs with both *over-estimation* and *over-precision* biases, plotting the change in the entry and exit error measures from the unbiased case (i.e., Figure 3). As Panel A shows, the *aggressive* policy generates much less mistaken entry for overconfident entrepreneurs than it

[16] Our results are robust to a range of other parameters; however when initial beliefs about new ideas are set too high, or when the agents become too over-precise, they cease to pivot and all value creation collapses for this set of pivot thresholds.

does for unbiased entrepreneurs. Indeed, the improvement is quite pronounced: while mistaken entry increases when these types of bias are introduced for the *conservative* and *balanced* policies, for X > 5, the *aggressive* policy generates less mistaken entry overall for biased entrepreneurs. This improvement more than compensates for the fact that the *aggressive* threshold generates more non-entry mistakes for overconfident entrepreneurs than it does for unbiased ones (Panel B). Panels C and D, respectively, show that biased entrepreneurs have slightly more exit delay when using the *aggressive* threshold and that conditional on entry with a type-H idea, they are less likely to mistakenly exit when using the *aggressive* threshold.

<INSERT FIGURE 5 ABOUT HERE>

Although the collective impact of these errors is subtle, the advantage of the *aggressive* program of experimentation for highly over-confident agents may also be understood intuitively as a bias-induced manifestation of the tradeoff between the number of experiments and the pivot threshold in the program of experimentation. Entrepreneurs who initially over-estimate the likelihood of success are likely to stick with a bad project for too long (i.e., gather "too much" information), especially when they are over-precise and hence update beliefs too slowly based on new data. Setting an *aggressive* performance threshold, i.e., requiring the belief that the current has a greater than 50% chance of success to be retained, limits the severity of this problem.

4.2.2 Optimal programs of experimentation as a function of bias

The simulations reported above suggest that the *aggressive* threshold outperforms the *balanced* and *conservative* thresholds for overconfident entrepreneurs, but it does not establish the threshold that optimizes performance for entrepreneurs with bias. In this subsection, we seek to identify this optimum and examine how it changes as a function of bias. We do so by comparing the outcomes of a series of simulations. The implication of this analysis is clear: Lean Startup principles, via the design of a suitable program of experimentation, have the potential to remedy many forms of bias.

Our interest is mainly in finding the optimal pivot threshold as a function of bias and the number of experiments; as such we focus our analysis on X = 2, 5, 10, and 20. Because overconfidence is not the only potential form of confidence bias, we extend our analysis to examine underconfidence. In particular, we examine nine combinations of biases: three levels of estimation bias resulting from initial beliefs of 0.4 (under-estimating likelihood of success), 0.5 (correctly estimating of likelihood of success), and 0.6 (over-estimating likelihood of success), and three precision settings of $\hat{\tau}/\tau = 0.5$ (updating beliefs too slowly), $\hat{\tau}/\tau = 1.0$ (updating beliefs correctly), and $\hat{\tau}/\tau = 2.0$ (updating beliefs too rapidly).

We display the simulation results in Figure 6. The top set of panels contains the optimal thresholds, and the bottom set reports the expected profit levels achieved at the optimal thresholds, relative to the never-pivot baseline for that pair of biases. In the top set of panels, we consider values above 0.5 corresponding to a more aggressive pivot threshold and values below 0.5 corresponding to a more conservative threshold. In the bottom set of panels, positive values indicate that, given X, the optimal threshold for this set of biases performs better for the biased agent than commitment to evaluating a single idea. In each panel, the central square represents an unbiased entrepreneur; the right (left) side of the panel reports simulation results for *over- (under-) estimation* bias; and the top (bottom) side of the panel examines *over- (under-) precision* bias.

<INSERT FIGURE 6 ABOUT HERE>

Several features of this figure are noteworthy. First, for unbiased entrepreneurs (the central squares), the optimal threshold takes the value of 0.53 for $X = 2$ and then declines below 0.50 for $X \geq 5$. Thus, for unbiased agents at this set of parameters, a conservative approach that generates fewer pivots dominates when X becomes sufficiently large. For these unbiased agents, as X increases, the optimal threshold falls, suggesting that a program of experimentation that yields a modest number of pivots in expectation maximizes value creation for the entrepreneur.[17]

[17] In additional analyses in the Online Appendix, we examine how changes in k affect these outcomes.

Second, the figure shows that, except for extreme cases of bias, programs of experimentation with optimal pivot thresholds generate better outcomes than committing to a single idea (see bottom panels). Of the 36 cases we examine, only *over-precise under-estimating* entrepreneurs are made worse off when choosing the threshold optimally, and this only occurs for $X = 20$. For all combinations of bias, programs of experimentation with optimal thresholds consistently create more value than committing to a single idea. Thus, the appropriate design of a program of experimentation has the potential to remedy many forms of bias.

Finally, we note two patterns in the optimal thresholds across different levels of bias. First, moving from left (*under-estimation, i.e., pessimistic*) to right (*over-estimation, i.e., optimistic*) we see that the optimal pivot threshold increases. Entrepreneurs who initially hold optimistic beliefs that a given idea will succeed are, indeed, better off choosing a pivot threshold that is (at least somewhat) aggressive. Intuitively speaking, the problem that plagues an optimistic entrepreneur is the overpursuit of type-L (bad) ideas, so it stands to reason that such an entrepreneur is better off being forced to pivot more aggressively. Second, moving from bottom (*under-precision*) to top (*over-precision*) within the panels, we see that the trend in the optimal pivot threshold depends on both the number of experiments and the type of estimation bias. With *under-estimation*, the optimal threshold is always increasing as the responsiveness to new information increases. With *over-estimation* no distinct pattern emerges. For $X = 2$ and $X = 5$ and *over-estimation*, the optimal threshold declines with precision bias; for $X = 10$ and $X = 20$, the pattern is reversed. In no case, however, does the value of the optimal threshold for *over-estimating* entrepreneurs fall below 0.5. This further strengthens our view, developed above, that aggressive pivot thresholds are better suited to addressing *over-estimation* bias.

Collectively, these simulation results support the claim that *pivoting is a remedy for bias*, or more specifically, the appropriate design of a program of experimentation can remedy bias. Further, the analyses show that the greater the degree of overconfidence, the more benefits accrue to a program of experimentation that pushes entrepreneurs to investigate more ideas.

4.3 Empirical implications

Increasingly, scholars have shown interest in empirical studies of pivoting, which naturally raises questions about empirical relationships between pivots and performance (e.g., Boddington and Kavadias 2018, Angus 2019, Kirtley and O'Mahoney 2020). Our model offers both context for hypothesizing empirical predictions about these relationships as well as some straightforward, testable predictions. Critically, it generates what might be interpreted as divergent normative and positive predictions. While our model shows a positive relationship between expected profits and the number of experiments as X increases from 1 to X^{max}, it does not imply that such an empirical relationship will exist between the number of pre-entry pivots (N) and the profits of entrepreneurs that *choose to enter* the market.

<INSERT FIGURE 7 ABOUT HERE>

In fact, the model implies the opposite. In Figure 7, we examine the relationship between pre-entry pivots and profitability for $X = 5$ for entrepreneurs that choose to enter the market after their period of pre-entry experimentation. We examine both unbiased entrepreneurs and those with behavioral biases. For each combination of biases, the average profit of entrants declines with an increase in the number of pre-entry pivots, regardless of the pivot threshold chosen. For the most part, for $N \geq 1$, average profits are near or below the values generated by entrants following a no-pivot policy (as shown by the dotted line). Thus, while each program of experimentation examined in the figure creates value on average relative to not experimenting (i.e., $X = 1$), an observer observing only those entrepreneurs that enter the market would be likely to uncover a negative empirical relationship between the number of pivots and performance.

The intuition behind this outcome highlights a dark side of frequent pivoting that has largely been overlooked: while having the option to pivot generates value for the entrepreneur, being faced with the necessity to actually pivot generally indicates that the present idea is not promising, and as pivots accumulate, less and less information is available to make effective market entry decisions.

4.4 Optimal time allocation and pivot threshold for unbiased entrepreneurs

In the sections above, we examine simulations with experiments of equal length. Although these simulations shed light on the linked question of whether entrepreneurs should *pivot early and often*, they do not allow us to disentangle issues of pivot timing from pivot frequency. In this section, we relax the assumption that all experiment periods during the pre-entry period have equal length, allowing us to more directly examine the question of whether early pivots are more beneficial than later ones. To do this, we fix $X = 2$, and ask, "how much time should the entrepreneur invest in examining an initial idea I_1 before considering a switch to a second idea I_2, and what pivot threshold should she choose to optimize profits?"

Setting $\Lambda = 1$, as in the simulations above, we vary the proportion of the pre-entry period devoted to examining I_1 from 0 to 1 in increments of 0.05 and evaluate how different pivot thresholds perform. For example, choosing a pivot time of 0.3 to divide the period means that the entrepreneur will consider switching from I_1 to I_2 at $t = -0.7$, which is earlier than the equal-length ($t = -0.5$) assumption in the previously reported experiments. Here an optimal pivot time of less than 0.5 can be interpreted as supporting early pivots, and an optimal pivot threshold greater than 0.5 could be interpreted as supporting the principle of *pivoting often*.

<INSERT FIGURE 8 ABOUT HERE>

Figure 8 plots the optimal timing for considering a pivot from I_1 to I_2 , i.e., the length of the first experiment relative to that of the second, as a function of the pivot threshold for unbiased entrepreneurs and for those exhibiting at least one form of overconfidence bias. Whether the entrepreneur is better off pivoting early or late depends on her pivot threshold. At low pivot thresholds (i.e., more conservative) the entrepreneur is better off running a longer first experiment, thus considering a pivot only near the end of the pre-entry learning time. By contrast, as pivot thresholds approach that of a *balanced* strategy (pivot threshold = 0.5), a shorter first experiment generates greater value. As these thresholds further increase, leading to a greater likelihood of pivoting, the optimal length of the first experiment, and the earliest possibility of pivoting, remains between 0.45 and 0.5, indicating that somewhat earlier pivots are better. This is true for both biased and unbiased entrepreneurs.

Figure 8 provides a second important take-away. Entrepreneurs exhibiting both *over-estimation* and *over-precision* bias should optimally consider a shorter first experiment providing the possibility to pivot earlier than unbiased entrepreneurs at every possible pivot threshold. For estimation bias alone, the pattern is different—these entrepreneurs are better off pivoting later when choosing pivot thresholds between 0.4 and 0.6. This pattern has a straightforward interpretation: when selecting a threshold that fosters more pivots, choosing to evaluate the idea (somewhat) early leads to greater value creation. Stated differently, this analysis suggests amending the proposition sometimes found in the Lean Startup movement to "when planning to pivot often, consider pivots early" More generally, these simulations suggest that a program of experimentation, which we have simplified to the number of experiments and the pivot threshold may be usefully extended to consider how time should be allocated across experiments.

5. DISCUSSION

Management scholars' long-standing interest in entrepreneurial learning has been rekindled by Lean Startup ideas. Prior to Ries (2011) and Blank (2013), entrepreneurship theories such as effectuation (Sarasvathy, 2001), bricolage (Baker and Nelson 2005), and concepts such as the entrepreneurial mindset (McGrath and MacMillan, 2000) anticipated key assumptions of the Lean Startup, in particular the iterative, uncertain, and experimental nature of entrepreneurial ventures. While such work has shed considerable light on *why* firms might employ a framework such as the Lean Startup methodology, it has spoken less strongly to the question of *how* one should do so. Our study provides an important building block in developing a richer theoretical foundation for the Lean Startup approach, extending the substantial body of work that has rapidly emerged over the past several years.

5.1 Program of experimentation

Our core claim is that entrepreneurs must design an effective *program of experimentation*. In our view, the basic logic of the Lean Startup, encapsulated in the idea of the build-measure-learn cycle, focuses not on the features of any particular experiment, or the capability of entrepreneurs to carry them out, but rather, on the design of the program defined as a sequentially interdependent set of experiments and pivots undertaken as an entrepreneur seeks to develop a viable business idea. When resources are constrained, in terms of the time or capital available for development, and the outcomes of experiments are ambiguous and uncertain, the entrepreneur faces (at least) two key choices in program design: the number of experiments to run and the pivot threshold for evaluating the experimental outcome as a success or failure.

How should entrepreneurs think about key choices in the design of a program of experimentation along these two dimensions? Ries (2011: p.8) notes that the Lean Startup does not provide a "clinical formula" for making pivot or persevere decisions, and likewise, Shepherd and Gruber (2021: p.980) highlight that the "important question facing founders is whether they should pivot or persevere, which is a challenging decision given that it is shrouded in uncertainty."

We have sought to offer some guidance in answer to the above question — not a clinical formula, but rather, a richer understanding of the core tradeoffs inherent in such decisions. The essence of this trade-off is simple — the more distinct experiments an entrepreneur plans to run, the shorter, and less informative, these experiments will become, which in turn changes how cautious the venture should be in evaluating the results. In recognizing this trade-off, our work connects the Lean Startup to the canonical exploration-exploitation problem in which learning more about an uncertain opportunity comes at a cost, financial and non-financial(Aghion et al., 1991; March, 1991; Posen and Levinthal, 2012).

Recognition of this trade-off stands in contrast to the popular wisdom on the Lean Startup, which may appear somewhat rigid and overly assured in its recommendations for the merits of aggressive pivoting. For instance, the practitioner literature recommends that entrepreneurs should pivot early rather than waiting to collect more information about the attractiveness of the idea. The Founder's Institute, a large pre-seed startup accelerator, states that "if you are going to pivot... you need to do it as early as possible, as this helps avoid wasting time, effort, and money." A related suggestion is that entrepreneurs should pivot often and aggressively to discover a good idea, reflecting how many successful new ventures moved quite far from their initial idea through a sequence of pivots. Alan Cooper, the creator of Visual Basic, argues that "when the cost to play the startup game is next to nothing, the cost of making mistakes is tiny, too, as is the cost to pivot … You can just keep having and trying ideas at little or no cost, and eventually one of them will be good enough." This disconnect between the popular wisdom and the trade-offs inherent in pivot or persevere decisions examined in our model highlights the value of developing a richer theoretical understanding of experimentation and learning in startups.

A key feature of our conceptualization of a program of experimentation is that the number and timing of *pivots* is an outcome rather than a choice variable — it is the *number of experiments* and the *pivot threshold* that together determine the when and how often a firm pivots. An entrepreneur that conducts many experiments and sets an aggressive pivot threshold will surely pivot frequently. However, doing so may well undermine learning and expected performance.

Our approach, premised on the design of the program of experimentation, opens up an avenue to understand if and how a program can be designed to overcome, in whole or in part, entrepreneurial bias. The literature on such bias, overconfidence in particular, is extensive, highlighted by the canonical contributions of Cooper, Woo, and Dunkelberg (1988), Busenitz and Barney (1997), and Camerer and Lovallo (1999). This work suggests that entrepreneurial bias is pervasive enough to make policy measures aimed at reducing it difficult, if not impossible. Our study suggests a novel approach to address such bias. Over-confident entrepreneurs should pick programs of experimentation that are more aggressive than those well-suited to unbiased entrepreneurs; the greater the overconfidence, the more the entrepreneur benefits from choosing rules that are too aggressive from the standpoint of an unbiased entrepreneur. Thus, instead of ‘fixing’ overconfident entrepreneurs, we can design a program of experimentation that compensates for their biases.

Moreover, as we noted above, popular wisdom seems to argue for aggressive pivoting behavior. Our findings imply that in contexts where aggressive pivoting outcomes are (perhaps inappropriately) demanded, it may be best to match such demands with over-confident entrepreneurs. Thus, promoting aggressive pivoting in entrepreneurial firms may be an indirect way of “fixing” over-confident entrepreneurs. Indeed, there may even be situations where aggressive pivoting, along with overconfident entrepreneurs, are essential to success, in line with Busenitz and Barney (p. 10), who speculate that “without the use of biases and heuristics, many entrepreneurial decisions would never be made.”

Our model further highlights empirical challenges in studying how pivoting behavior affects performance. First, entrepreneurs’ choices in the design of their programs of experimentation will typically not be observable by empirical researchers, yet, as our model shows, they critically influence behavior and performance post entry. Second, we show that endogenous selection inherent in the entry (scale-up) decision induces a negative relationship between the observed number of pivots and success in the marketplace, regardless of pivot threshold. Put quite simply, pivoting a lot can reflect bad luck rather than bad decision-making, and those who (correctly) pivoted many times have less information about each idea from which to make an effective entry decision. Thus, researchers examining pivot-performance relationships, e.g. legitimacy with stakeholders (McDonald and Gao 2019), may wish to examine the possibility of selection as an alternative explanation.

Furthermore, our study complements and extends empirical research focused on experimentation and pivoting. Scholars have examined whether Lean Startup elements that are held to inform pivot decisions, such as customer probing or A/B testing, actually do so

(Leatherbee and Katila 2020; Koning, Hasan and Chatterji 2022; Camuffo, Cordova, Gambardella and Spina 2020). Other work explores whether the propensity to pivot is affected by various biases entrepreneurs might hold on ideas, such as that engendered by skewed participant feedback (Cao, Koning, and Nanda 2021), identifying with an idea too strongly (Grimes 2018, Hampel, Tracey and Weber 2020), or an overreliance on readily observable feedback (Felin, Gambardella, Stern and Zenger 2020). Our work, in contrast, points to the importance of empirical research that (a) evaluates the effectiveness of alternative programs of experimentation — in particular the sensitivity of entrepreneurs to "bad news" in deciding whether to pivot or persist — and (b) examines the interaction of these with overconfidence biases.

5.2 Boundary conditions, limitations, and future modeling directions

Our model has numerous assumptions and restrictions that bound its predictions. Three key simplifying assumptions are worth mentioning. First, we assume that ideas are unchanging. Significant scholarly attention has examined how ideas are shaped, improved, or legitimized as entrepreneurs expose them to different audiences (Wry, Lounsbury, and Glynn 2011; Lounsbury and Glynn 2019). In our conceptualization, changing any key aspect of the business model means testing a new idea. Ideas themselves cannot be improved, and all pivots are equivalent, whether they involve changing a single element of the business model or many. Our model can easily be extended to a scenario in which entrepreneurs evaluate multiple *components* of a plan with independent signals, and evaluate entry at the end of a fixed learning period. So long as the individual components and signals are independent, the main outcomes of our model hold, although entry rates fall as the number of components needed for a successful product launch increases. An alternative approach would be to construct a model with a series of related choices that could vary in magnitude of impact and cost and would, therefore, distinguish between large and small pivots. We think of this approach as promising, but beyond the scope of our present work.

A second, and related, assumption is that ideas are independent. This assumption is easily relaxed in the model. A natural alternative assumption would be that, with experience, the entrepreneur gets better at selecting an idea on which to experiment. As a consequence Pr(I_j = type-H) < Pr(I_{j+1} = type-H). Figure C2 in the Online Appendix provides the outcomes of this model under the assumption that Pr(I_1 = type-H) = 0.50 and Pr(I_{j+1} = type-H) - Pr(I_j = type-H) = 0.005, for each $j \in [1, 19]$. Predictably, it makes pivoting (and more aggressive pivot strategies) more attractive.

Third, we assume that learning by experimentation is only possible in the pre-entry period. After entry, entrepreneurs are committed to one idea that cannot be improved. They continue to learn about its quality, updating their beliefs as the result of the profits and losses the venture generates. They have the option to terminate the business and receive future payouts of zero, which is equivalent, given our baseline parameters, to launching a new idea with a 0.5 probability of being type H. A potential extension would be to allow the entrepreneur to improve her odds of success post entry. This would have the natural consequence of making entry more attractive, but would be likely to make pre-entry experimentation less attractive. We leave extensions of this sort for future work.

We note a handful of additional limitations, but do not claim to be exhaustive. For instance, our model assumes that entrepreneurs have limited resources, which caps the length of the pre-entry period. We believe this assumption maps to the entrepreneurial reality that firms cannot survive indefinitely without a product-market-based source of funds. Learning occurs passively in our model rather than as the result of effort or investment, which would require additional optimization considerations (see Pakes and Ericson 1998 for a discussion). When it comes to bias, we ignore the possibility that optimism can affect not only whether the entrepreneur exploits an opportunity, but also how (e.g., Dushnitsky 2010), and we neglect alternative mechanisms that lead to overconfidence, such as asymmetric updating or confirmatory bias, which have been shown to be empirically important in both field and laboratory studies of exit delay (Elfenbein and Knott 2015, Elfenbein, Knott, and Croson 2017), or anchoring bias, which has been examined in survey-based work (Simon, Houghton, and Aquino 2000). While our model is amenable to examining the impact of these, and other, biases, we leave their analysis for future work.

5.3 Concluding Remarks

Pivoting is a central concept in the Lean Startup approach, yet the answers to who benefits from pivoting, and precisely when and how much they should do so, remains poorly understood. Our parsimonious computational model shows that entrepreneurial learning strategies that incorporate potential pivots do improve performance, and that the right program of experimentation can be particularly valuable for overconfident entrepreneurs. The model highlights the role of the design of the *program of experimentation*, and the critical tradeoff in that the more distinct experiments an entrepreneur plans to run, the shorter, and less informative, these experiments must become, which in turn changes how cautious the venture should be in evaluating the results. Thus programs of experimentation that generate frequent and early pivots may impede learning and underperform more conservative approaches that generate fewer pivots.

6. REFERENCES

Agrawal A, Gans JS, Stern S. 2021. Enabling entrepreneurial choice. *Management Science*. 67(9): 5510-5524.

Aghion P, Bolton P, Harris C, Jullien B. 1991. Optimal learning by experimentation. *The Review of Economic Studies*. 58(4): 621-654.

Angus RW. 2019. Problemistic search distance and entrepreneurial performance. *Strategic Management Journal.* 40(12): 2011–2023.

Argote L. 1999. *Organizational learning: Creating, retaining, and transferring knowledge*. Kluwer Academic Publishers; Boston.

Baker T, Nelson RE. 2005. Creating something from nothing: Resource construction through entrepreneurial bricolage. *Administrative Science Quarterly*. *50*(3): 329-366.

Bennett VM, Chatterji AK. 2019. The entrepreneurial process: Evidence from a nationally representative survey. *Strategic Management Journal*. 1-31.

Bingham CB, Davis JP. 2012. Learning sequences: Their existence, effect, and evolution. *Academy of Management Journal. 55*(3): 611-641.

Bland DJ, Osterwalder A. 2019. *Testing business ideas: A field guide for rapid experimentation* (Vol. 3). John Wiley & Sons.

Blank S. 2013. Why the Lean Startup changes everything. *Harvard Business Review. 91*(5): 63-72.

Bocken N, Snihur Y. 2020. Lean Startup and the business model: Experimenting for novelty and impact. *Long Range Planning*. *53*(4). 101953.

Boddington M, Kavadias S. 2018. Entrepreneurial pivoting as organizational search: Defining pivoting in early stage ventures. *Academy of Management Proceedings*

Busenitz LW and Barney JB. 1997. Differences between entrepreneurs and managers in large organizations: Biases and heuristics in strategic decision-making. *Journal of Business Venturing. 12*(1): 9-30.

Cain DM, Moore DA, Haran U. 2015. Making sense of overconfidence in market entry. *Strategic Management Journal*. *36*(1): 1–18.

Camerer C, Lovallo D. 1999. Overconfidence and excess entry: An experimental approach. *American Economic Review.* 89(1): 306-318.

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.

Chen JS, Croson DC, Elfenbein DW, Posen HE. 2018. The impact of learning and overconfidence on entrepreneurial entry and exit. *Organization Science.* 29(6): 989-1009.

Chen JS, Elfenbein DW, Posen HE, Wang MZ. 2022. The problems and promise of entrepreneurial partnerships: Organizational design, overconfidence, and learning in founding teams. *Academy of Management Review. Forthcoming.*

Contigiani, A. 2020. Experimental Learning in Early-Stage Ventures. Available at SSRN: https://ssrn.com/abstract=3727500

Contigiani A, Levinthal DA. 2019. Situating the construct of lean start-up: adjacent conversations and possible future directions. *Industrial and Corporate Change.* 28(3): 551-564.

Contigiani, A, Young-Hyman, T. 2021. Experimentation, Planning, and Structure in Early‐Stage Ventures: Evidence from Venture Pitches. *Strategic Entrepreneurship Journal*. Forthcoming.

Cooper AC, Woo CY, Dunkelberg WC. 1988. Entrepreneurs' perceived chances for success. *Journal of Business Venturing. 3*(2): 97-108.

Cope J. 2005. Toward a dynamic learning perspective of entrepreneurship. *Entrepreneurship Theory and Practice. 29*(4): 373-397.

Cyert RM, March JG. 1963. *A behavioral theory of the firm*. Englewood Cliffs, N.J: Prentice-Hall.

Denrell J, March JG. 2001. Adaptation as information restriction: The hot stove effect. *Organization Science. 12*(5): 523–538.

Dushnitsky G. 2010. Entrepreneurial optimism in the market for technological inventions. *Organization Science. 21*(1): 150-167.

Eesley, C, Wu, L. 2020. For Startups, Adaptability and Mentor Network Diversity Can be Pivotal: Evidence from a Randomized Experiment on a MOOC Platform. *MIS Quarterly. 44*(2): 661-697.

Eisenmann TR, Ries E, Dillard S. 2013. Hypothesis-driven entrepreneurship: The Lean Startup. HBS No. 9-812-095. Boston, MA: Harvard Business School Publishing.

Elfenbein DW, Knott AM. 2015. Time to exit: rational, behavioral, and organizational delays. *Strategic Management Journal. 36*(7): 957-975.

Elfenbein DW, Knott AM, Croson R. 2017. Equity stakes and exit: An experimental approach to decomposing exit delay. *Strategic Management Journal. 38*(2): 278-299.

Felin T, Gambardella A, Stern S, Zenger T. 2020. Lean startup and the business model: Experimentation revisited. *Long Range Planning* 53(4).

Foss NJ, Klein PG, Bjørnskov C. 2019. The context of entrepreneurial judgment: organizations, markets, and institutions. *Journal of Management Studies*. *56*(6): 1197-1213.

Gans JS, Stern S, Wu J. 2019. Foundations of entrepreneurial strategy. *Strategic Management Journal*. *40*(5): 736–756.

Grimes MG. 2018. The pivot: How founders respond to feedback through idea and identity work. *Academy of Management Journal. 61*(5): 1692–1717.

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

Hamilton BH. 2000. Does entrepreneurship pay? An empirical analysis of the returns to self-employment. *Journal of Political Economy. 108*(3): 604-631.

Hampel CE, Tracey P, Weber K. 2020. The Art of the pivot: How new ventures manage identification relationships with stakeholders as they change direction. *Academy of Management Journal*. *63*(2): 440–471.

Hayward ML, Shepherd DA, Griffin D. 2006. A hubris theory of entrepreneurship. *Management Science. 52*(2): 160-172.

Holland JH. 1975. *Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control & Artificial Intelligence*. Michigan Univ. Press.

Kerr WR, Nanda R, Rhodes-Kropf M. 2014. Entrepreneurship as experimentation. *Journal of Economic Perspectives. 28*(3): 25-48.

Kirtley J, O'Mahony S. 2020. What is a pivot? Explaining when and how entrepreneurial firms decide to make strategic change and pivot. *Strategic Management Journal.*

Leatherbee M, Katila R. 2020. The Lean Startup method: Early-stage teams and hypothesis-based probing of business ideas. *Strategic Entrepreneurship Journal. 14*(4): 570-593.

Levinthal DA, March JG. 1993. The myopia of learning. *Strategic Management Journal. 14*(S2): 95–112.

Levinthal DA, Posen HE. 2007. Myopia of selection: Does organizational adaptation limit the efficacy of population selection? *Administrative Science Quarterly. 52*(4): 586–620.

Loch CH, Terwiesch C, Thomke S. 2001. Parallel and sequential testing of design alternatives.

Management Science. 47(5): 663-678.
Lounsbury M, Glynn MA. 2001. Cultural entrepreneurship: Stories, legitimacy, and the acquisition of resources. *Strategic Management Journal*. *22*(6‐7): 545-564.
Lounsbury M, Glynn MA. 2019. *Cultural Entrepreneurship: A New Agenda for the Study of Entrepreneurial Processes and Possibilities*. Cambridge University Press;
Lowe RA, Ziedonis AA. 2006. Overoptimism and the performance of entrepreneurial firms. *Management Science. 52*(2): 173-186.
Makadok, R, Burton, R, Barney, J. 2018. A practical guide for making theory contributions in strategic management. *Strategic Management Journal* 39(6): 1530-1545.
Manso G. 2016. Experimentation and the Returns to Entrepreneurship. *The Review of Financial Studies. 29*(9): 2319-2340.
March JG. 1991. Exploration and exploitation in organizational learning. *Organization Science. 2*(1): 71–87.
March JG, Sproull LS, Tamuz M. 1991. Learning from samples of one or fewer. *Organization Science*. *2*(1): 1–13.
Mauer R, Wuebker R, Schlüter J, Brettel M. 2018. Prediction and control: An agent‐based simulation of search processes in the entrepreneurial problem space. *Strategic Entrepreneurship Journal*. *12*(2): 237–260.
McDonald RM, Eisenhardt KM. 2020. Parallel play: Startups, nascent markets, and effective business-model design. *Administrative Science Quarterly*. *65*(2): 483-523.
McDonald R, Gao C. 2019. Pivoting isn't enough? Managing strategic reorientation in new ventures. *Organization Science. 30*(6): 1289–1318.
McGrath, RG, MacMillan, IC. 2000. *The Entrepreneurial Mindset: Strategies for Continuously Creating Opportunity in an Age of Uncertainty*. Harvard Business Press.
Minniti M, Bygrave W. 2001. A dynamic model of entrepreneurial learning. *Entrepreneurship Theory and Practice. 25*(3): 5-16.
Moore DA, Healy PJ. 2008. The trouble with overconfidence. *Psychological Review. 115*(2): 502-517.
Murray F, Tripsas M. 2004. The Exploratory Processes of Entrepreneurial Firms: The Role of Purposeful Experimentation. In *Advances in Strategic Management* 21, A.C. Baum, J, M. McGahan, A (eds). Emerald Group Publishing Limited: 45-75.
Nanda R, Rhodes-Kropf M. 2016. Financing entrepreneurial experimentation. *Innovation Policy and the Economy*. *16*(1): 1-23.
Navis C, Glynn MA. 2011. Legitimate distinctiveness and the entrepreneurial identity: Influence on investor judgments of new venture plausibility. *Academy of Management Review. 36*(3): 479-499.
Nelson RR, Winter SG. 1982. *An Evolutionary Theory of Economic Change*. Harvard University Press.
Pakes A, Ericson R. 1998. Empirical implications of alternative models of firm dynamics. *Journal of Economic Theory. 79*(1): 1-45.
Posen HE, Chen JS. 2013. An advantage of newness: Vicarious learning despite limited absorptive capacity. *Organization Science*. *24*(6): 1701-1716.
Posen HE, Leiblein MJ, Chen JS. 2018. Toward a behavioral theory of real options: Noisy signals, bias, and learning. *Strategic Management Journal. 39*(4): 1112-1138.

Posen HE, Levinthal DA. 2012. Chasing a moving target: Exploitation and exploration in dynamic environments. *Management Science. 58*(3): 587–601.

Ries E. 2011. *The Lean Startup*. *How Today's Entrepreneurs Use Continuous Innovation to Create Radically Successful Businesses*. Crown Publishing Group.

Ries E. 2017. *The Startup Way: How Modern Companies Use Entrepreneurial Management to Transform Culture and Drive Long-term Growth.* Currency.

Rosenberg N. 1994. *Exploring the Black Box: Technology, Economics, and History*. Cambridge University Press.

Ryan R, Lippman SA. 2003. Optimal exit from a project with noisy returns. *Probability in the Engineering and Informational Sciences. 17*(4): 435-458.

Sandri S, Schade C, Musshoff O, Odening M. 2010. Holding on for too long? An experimental study on inertia in entrepreneurs' and non-entrepreneurs' disinvestment choices. *Journal of economic behavior & organization. 76*(1): 30-44.

Sarasvathy S. 2001. Causation and Effectuation: Toward a Theoretical Shift from Economic Inevitability to Entrepreneurial Contingency. *The Academy of Management Review. 26*(2): 243-263.

Shelef O, Wuebker R, Barney JB. 2020. Heisenberg Effects In Experiments On Business Ideas. Available at SSRN: https://ssrn.com/abstract=3581255

Shepherd, DA, Gruber, M. 2021. The Lean Startup Framework: Closing the Academic–Practitioner Divide. *Entrepreneurship Theory and Practice*. *45*(5): 967-998.

Simon M, Houghton SM, Aquino K. 2000. Cognitive biases, risk perception, and venture formation: How individuals decide to start companies. *Journal of Business Venturing. 15*(2): 113-134.

Woo CY, Daellenbach U, Nicholls-Nixon C. 1994. Theory building in the presence of 'randomness': The case of venture creation and performance. *Journal of Management Studies. 31*(4): 507-524.

Wry T, Lounsbury M, Glynn MA. 2011. Legitimating Nascent Collective Identities: Coordinating Cultural Entrepreneurship. *Organization Science. 22*(2): 449-463.

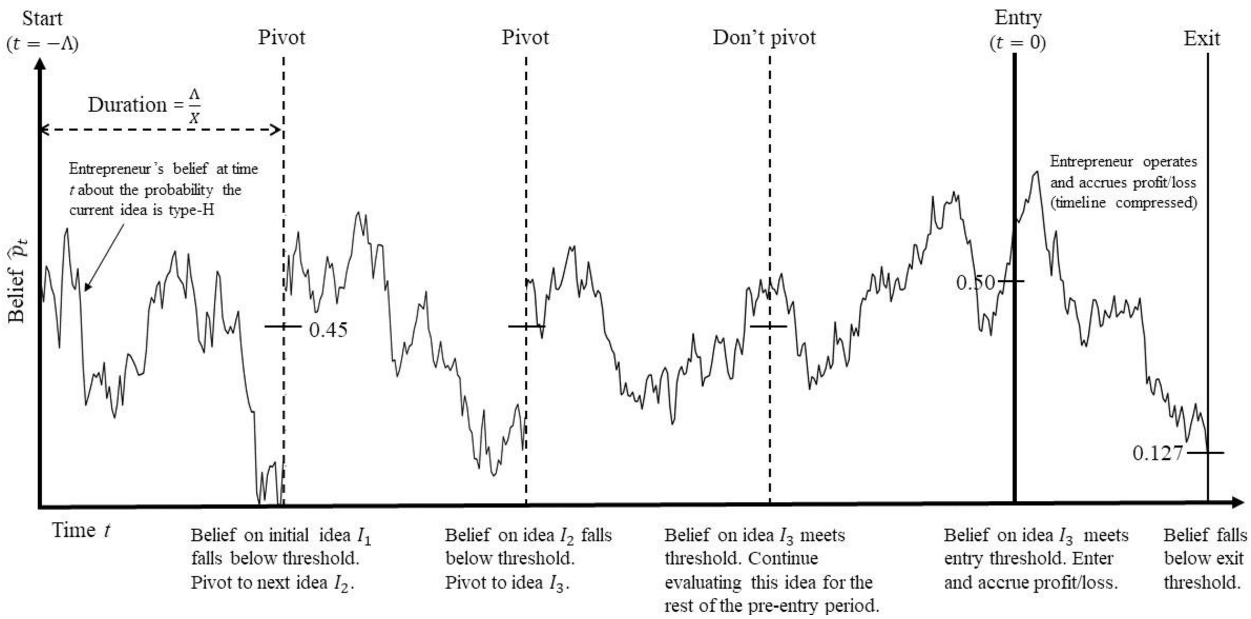
7. TABLES & FIGURES

Table 1. Overview of Computational Model

ASSUMPTIONS	MECHANISMS	OUTPUT & OUTCOMES

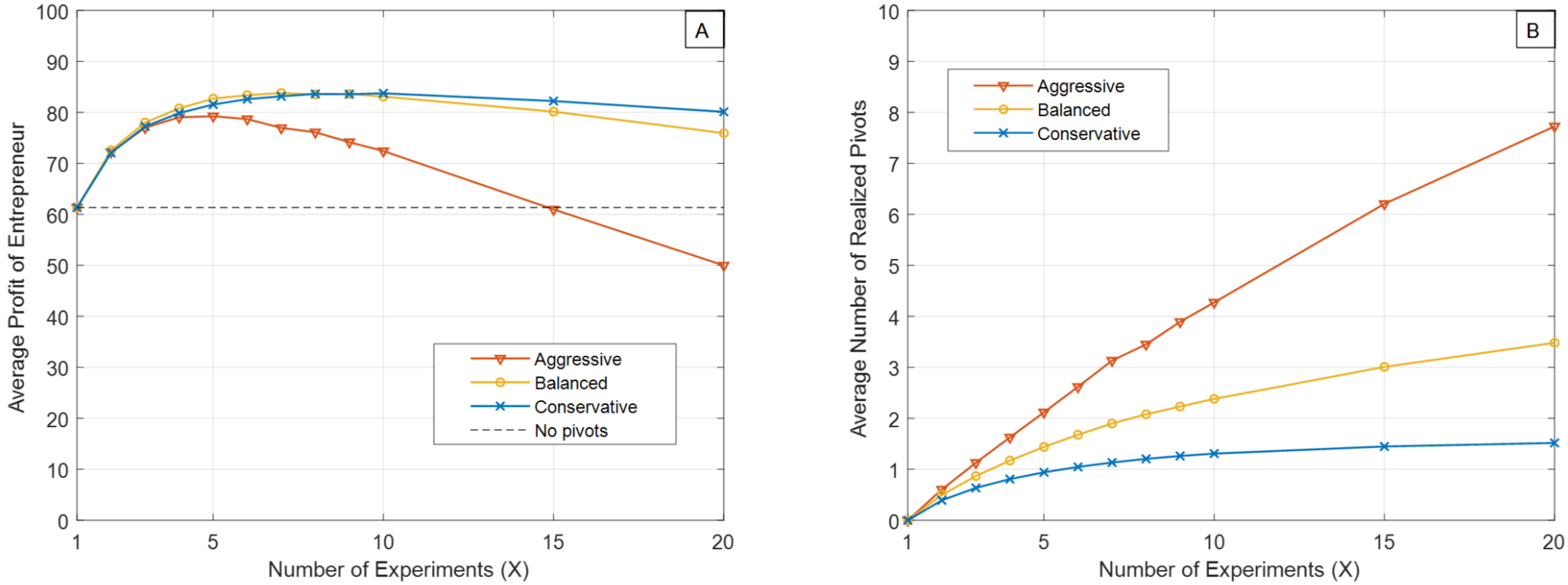
<u>Timing</u>
• Entrepreneurs receive costless signals about the profitability of potential business ideas from $t = -\Lambda$ to $t = 0$ (*pre-entry*).
• At $t = 0$, the entrepreneur must make an entry decision.
• If the entrepreneur enters at $t = 0$, she receives profits / losses based on her decision. She may choose to exit if her accrued profits / losses indicate that she should do so (*post-entry*).
 	
<u>Ideas</u>
• All ideas, $I_1, I_2, \ldots, I_N$, are of unknown quality *ex ante*, either type-H (profitable) or type-L (unprofitable).
 	
<u>Entrepreneur</u>
• Entrepreneur starts out with an initial idea, I_1
• Entrepreneur can only learn about one idea at a time.
• Entrepreneur commits to a pivot strategy at the onset.
• Between experiments, entrepreneur chooses to stick with her current idea, I_j or to begin experimenting with a new idea, I_{j+1}.
• Entrepreneur chooses whether to enter with the idea she believes to be best among the pre-entry ideas she investigated.
 	
Unbiased Entrepreneur
• Initial beliefs about Pr(Type = H) correct for each idea.
• Entrepreneur updates beliefs (learns) correctly given the noisiness of the profit signals.
 	
Overconfident Entrepreneur
• *Over-estimation.* Initial belief about Pr(Type = H) is too high for each idea.
• *Over-precision.* Entrepreneur updates beliefs too slowly given the noisiness of the profit signals.
 	
Underconfidenct Entrepreneur
• *Under-estimation.* Initial belief about Pr(Type = H) is too low for each idea.
• *Under-precision.* Entrepreneur updates beliefs too quickly given the noisiness of the profit signals.
	<u>Program of Experimentation</u>
	• A program of experimentation involves the following choices:
	  o The number of experiments to run, X
	  o The pivot threshold, θ, which is the belief about Pr(Type = H) below which an entrepreneur will pivot to a new idea:
	    ▪ ***Conservative*** threshold is $\theta = 0.45$.
	    ▪ ***Balanced*** threshold is $\theta = 0.50$.
	    ▪ ***Aggressive*** threshold is $\theta = 0.55$.
	
	<u>Experiments vs. Pivots</u>
	• Each experiment requires time, κ_a, to set up and evaluate.
	• Each pivot decision consumes additional time, κ_p, which reflects the costs required to generate tests for a new idea
	• The number of actual pivots, N, is a function of X, the pivot threshold, and these pivot costs ($N < X$).
	
	<u>Market Entry and Exit</u>
	• Entrepreneurs make entry and exit decisions that maximize profits, conditional on their beliefs.
	• Entrepreneurs enter only if beliefs about Pr(Type = H) correspond to an expected value that exceeds entry cost.
	• Post-entry, exit only if beliefs about Pr(Type = H) fall below the optimal exit threshold.
	
	<u>Errors</u>
	• Misleading profit signals may lead to the following errors of entry and exit:
	  o Mistaken entry with a type-L idea
	  o Mistaken non-entry with a type-H idea
	  o Post-entry, exit delay (i.e. remaining in the market) with a type-L idea
	  o Post-entry, mistaken exit with a type-H idea
		<u>Model Output</u>
		• For each population of entrepreneurs, the model produces:
		  o Number of pivots taken.
		  o Proportion of entry and exit errors.
		  o Time spent by each entrant in the market.
		  o Expected profits, net of entry cost.
		
		<u>Key Outcomes about Programs of Experimentation</u>
		• Programs of experimentation have the potential to generate significant improvement over commitment to a single idea for unbiased entrepreneurs, and for entrepreneurs with a broad range of biases.
		• Programs of experimentation that generate frequent and early pivots may impede learning and underperform more conservative approaches that generate fewer or later pivots.
		• Relative to an unbiased entrepreneur, an over-estimating entrepreneur optimizes performance by choosing a more aggressive pivot threshold, but not necessarily a higher number of experiments.
		• When selecting a pivot threshold that fosters more pivots, choosing to evaluate the idea earlier leads to greater value creation.
		
		<u>Other Outcomes</u>
		• Negative relationship between the number of pre-entry pivots and post-entry profits and success.
		• The higher the entry costs (reflecting greater financial risk) the lower, i.e., more *conservative,* is the optimal pivot threshold.

Figure 1. Timing and Representative Outcomes for X = 4



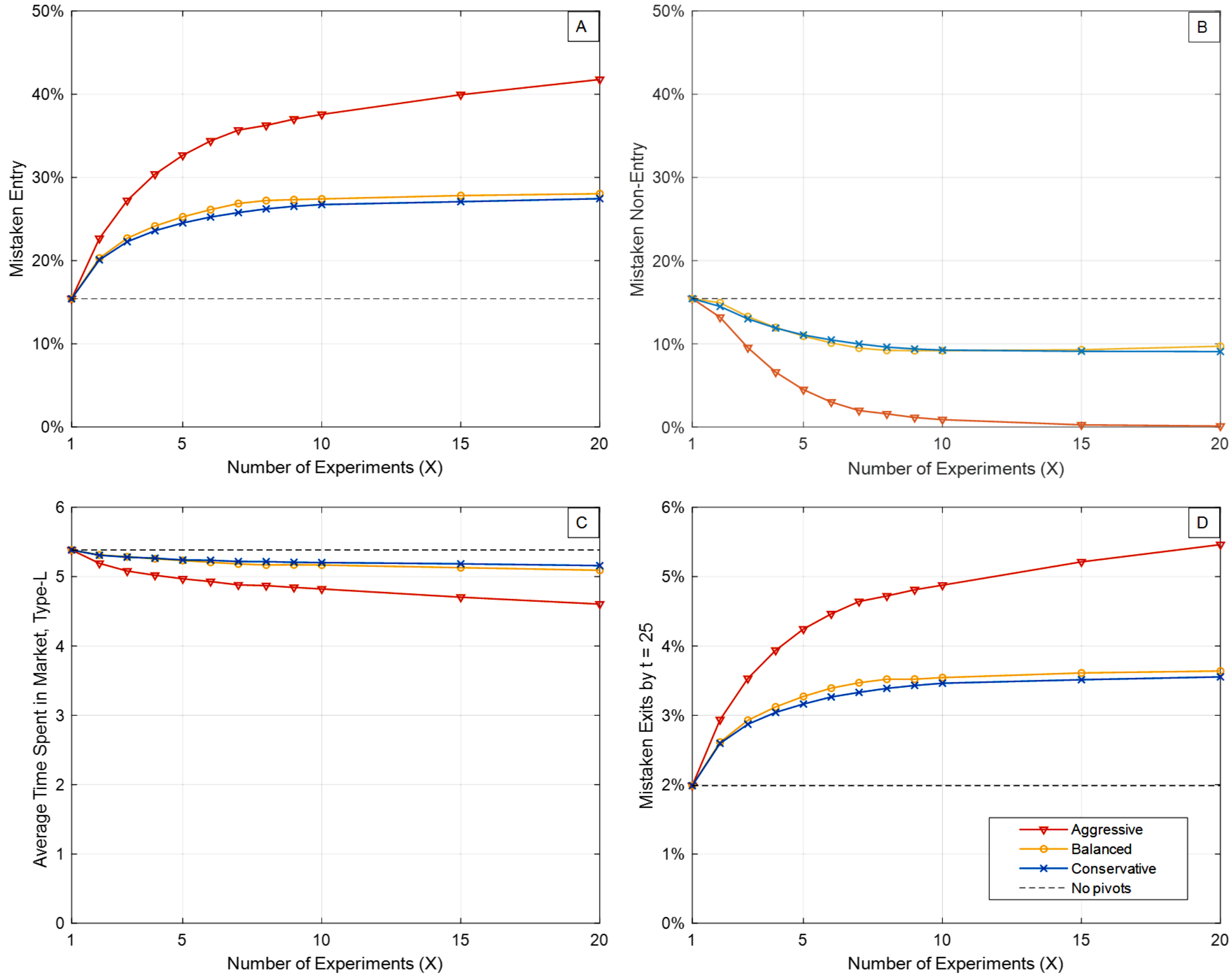
Notes: This figure shows the evolution of an entrepreneur's beliefs about the probability the idea is type-H, when she employs conservative pivot threshold of 0.45 and $X = 4$ ideas available. Notice the belief on idea I_3 is just below 0.5 at the time of its pivot decision, so under either a moderate (threshold = 0.5) or aggressive (threshold = 0.55) policy, the entrepreneur would have pivoted to idea I_4 rather than continue with I_3, as shown in the figure. The figure also shows the baseline scenario of $k = 153.7$, meaning the entrepreneur must believe that at least one idea, I_m, has Pr(I_m = type-H) of 0.5 or greater at t = 0 to enter. Since belief on idea I_3 is approximately 0.53 at time of entry. Under the low entry cost scenario ($k = 100$), this entry threshold would be 0.404, in which case the entrepreneur would still enter. Under the high entry cost scenario ($k = 200$), this entry threshold would be 0.577, in which case the entrepreneur would not enter. Per Ryan and Lippman (2003), the exit threshold is a function of μ_H, μ_L, δ, and σ, all of which are fixed in this study. Thus, for the parameter values we employ, the exit threshold is 0.127 across all experiments with unbiased agents in this study.

Figure 2. Performance and Realized Pivots as a Function of Pivot Threshold and Number of Experiments



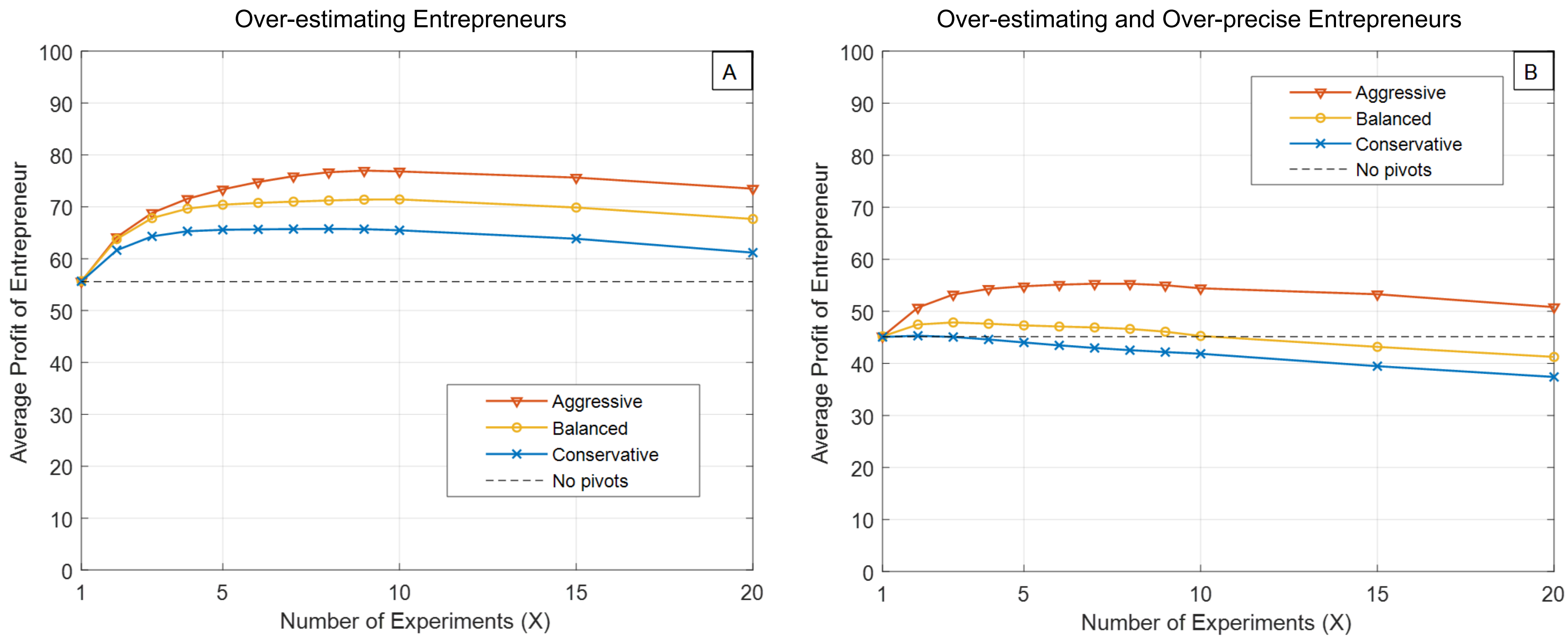
Notes: For each program of experimentation, we simulate 10,000,000 unbiased entrepreneurs and plot the average performance (left) and number of realized pivots (right) while varying the number of experiments the entrepreneurs conduct to evaluate their current idea. The *conservative*, *balanced*, and *aggressive* pivot thresholds are 0.45, 0.50, and 0.55, respectively. Number of experiments (X) ranges from 1 to 20. We set $\Lambda = 1$, $\kappa_p = 0.05$, $\kappa_a = 0.01$, and $k = 153.7$. The dotted line in the left panel plots the average performance of an entrepreneur who never pivots because she conducts only one experiment with her initial idea.

Figure 3. Entry and Exit Errors as a Function of Pivot Threshold and Number of Experiments



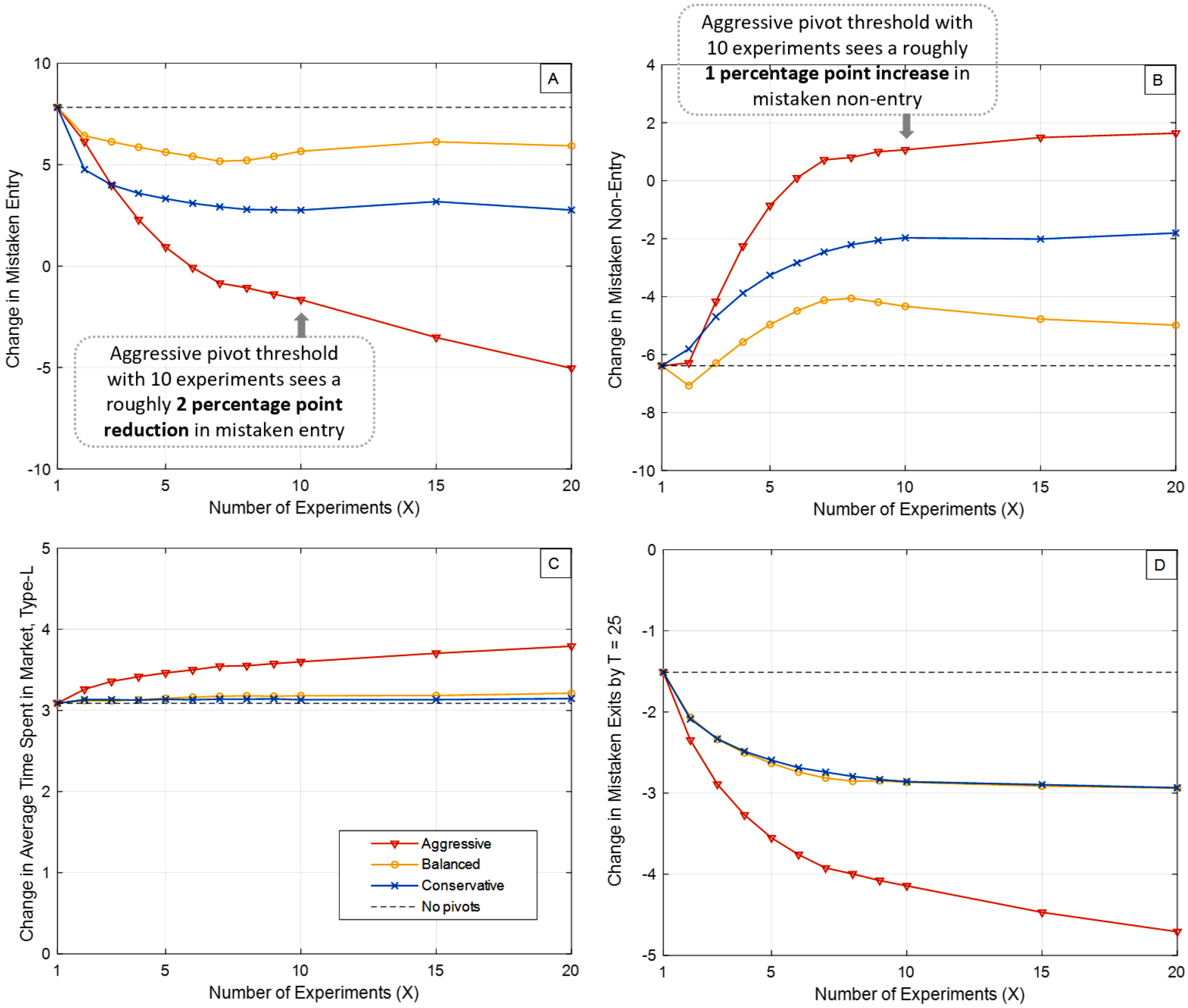
Notes: For each program of experimentation, we plot the measure corresponding to each panel's vertical axis label for 10,000,000 simulated unbiased entrepreneurs while varying the number of experiments the entrepreneurs conduct to evaluate their current idea. The *conservative*, *balanced*, and *aggressive* pivot thresholds are 0.45, 0.50, and 0.55, respectively. Number of experiments (*X*) ranges from 1 to 20. We set $\Lambda = 1$, $\kappa_p = 0.05$, $\kappa_a = 0.01$, and $k = 153.7$. The dotted line plots the average performance of an entrepreneur who never pivots because she conducts only one experiment with her initial idea. Panel A shows the share of entrepreneurs who enter with type-L ideas. Panel B depicts the share of entrepreneurs who encountered a type-H idea but failed to enter. Panel C shows the average number of periods that type-L entrants spend in the market before exiting. Panel D plots the share of entrepreneurs who enter with a type-H idea and mistakenly exit by $t = 25$.

Figure 4: Performance as a Function of Pivot Threshold and Number of Experiments for Over-estimating and Both Over-estimating and Over-precise Entrepreneurs



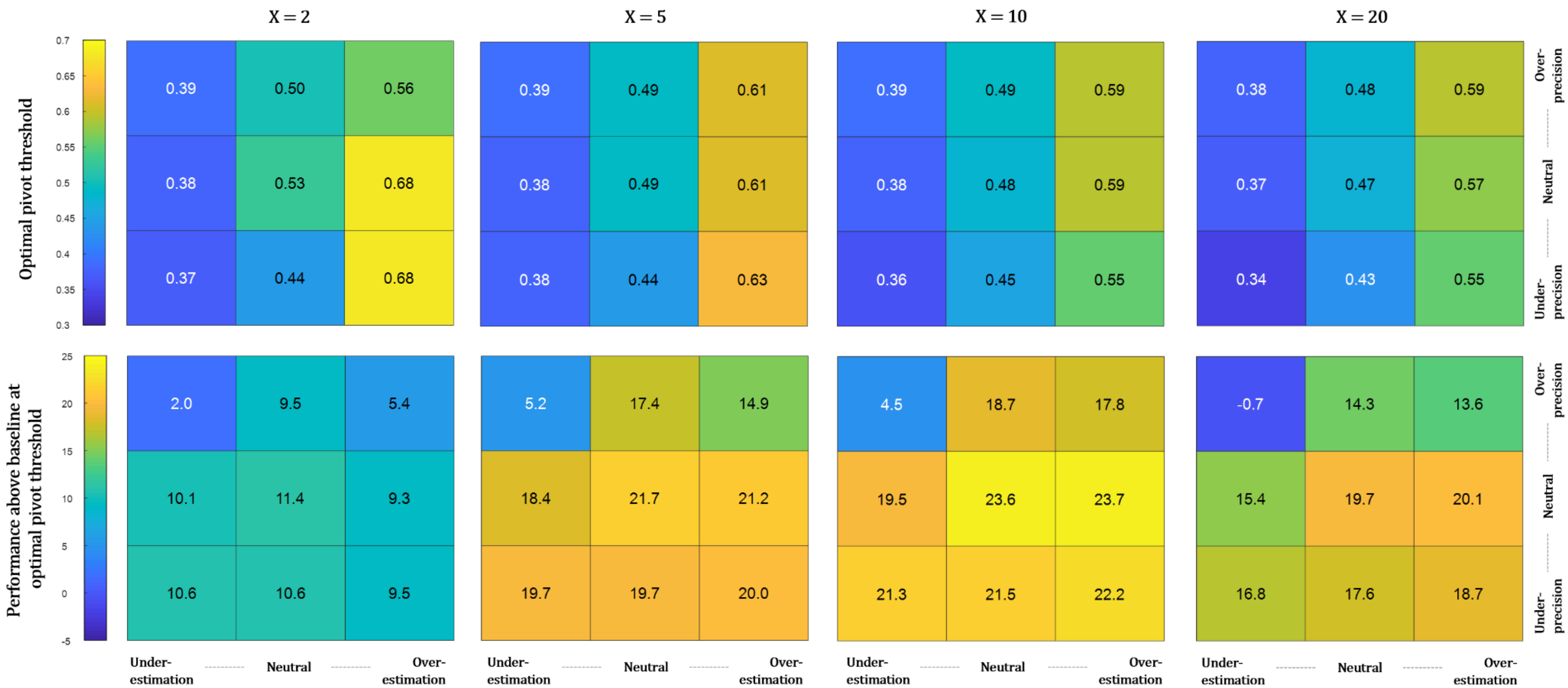
Notes: For each program of experimentation, we simulate 10,000,000 simulated unbiased entrepreneurs and plot the average performance with over-estimation bias (left) and with both over-estimation and over-precision biases (right) while varying the number of experiments the entrepreneurs conduct to evaluate their current idea. The *conservative*, *balanced*, and *aggressive* pivot thresholds are 0.45, 0.50, and 0.55, respectively. Number of experiments (X) ranges from 1 to 20. We set $\Lambda = 1$, $\kappa_p = 0.05$, $\kappa_a = 0.01$, and $k = 153.7$. To simulate over-estimation bias, we set $\hat{p}^{init} = 0.6$, and to simulate over-precision bias, we set $\hat{\tau}/\tau = 0.5$. The dotted line in each panel plots the average performance of an entrepreneur with the indicated biases who never pivots because she conducts only one experiment with her initial idea.

Figure 5: Effect of Overconfidence Biases on Entry and Exit Errors Across Programs of Experimentation



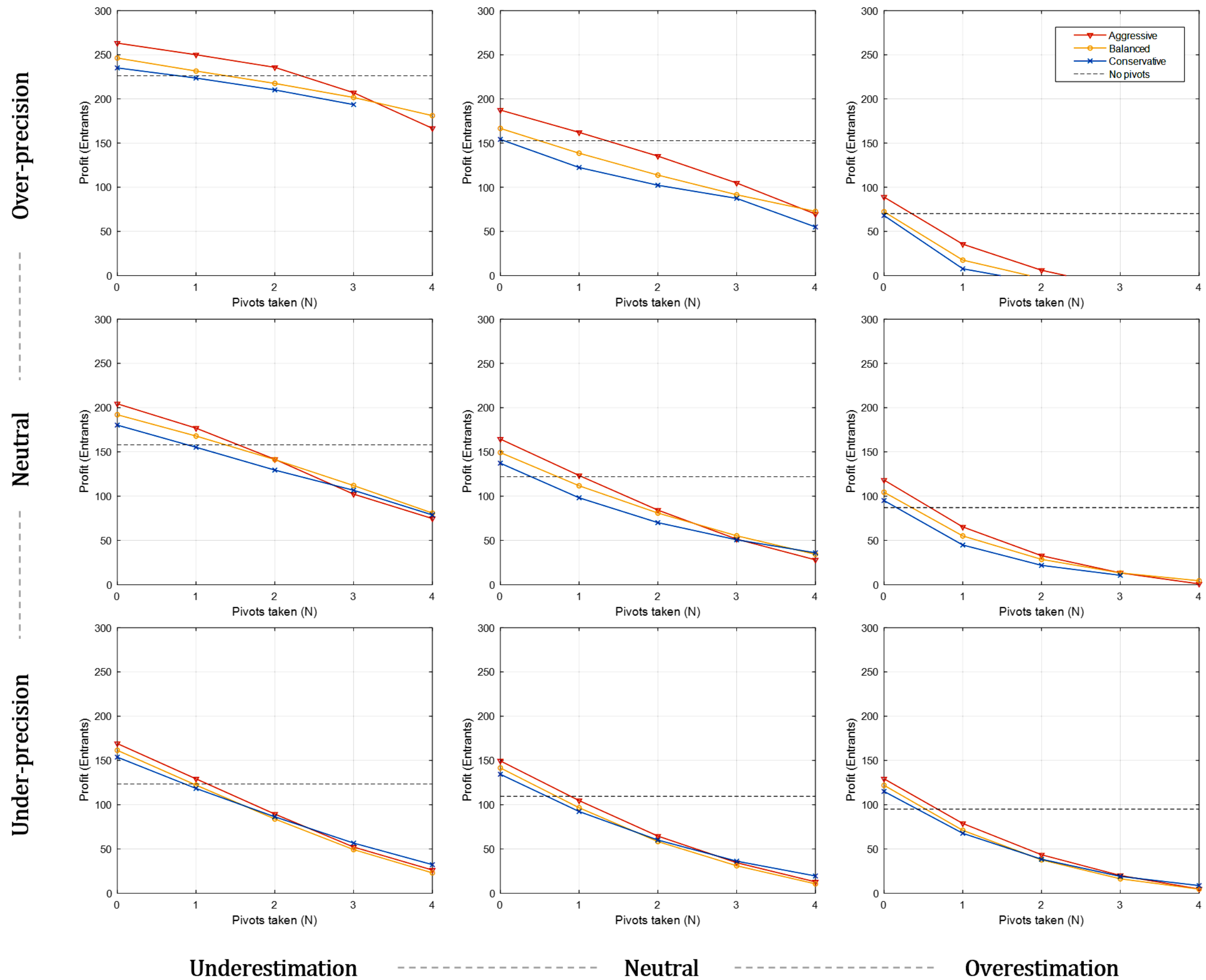
Notes: For each program of experimentation, we plot the change in the entry and exit error measures from Figure 3 when we introduce over-estimation and over-precision biases. To simulate over-estimation and over-precision bias, we set $\hat{p}^{init} = 0.6$ and $\hat{\tau}/\tau = 0.5$, respectively. The dotted line plots the change in the average performance of an entrepreneur who never pivots because she conducts only one experiment with her initial idea. Panel A shows the change in the share of entrepreneurs who enter with type-L ideas. Panel B depicts the change in share of entrepreneurs who encountered a type-H idea but failed to enter. Panel C shows the change in the average number of periods that type-L entrants spend in the market before exiting. Panel D plots the change in the share of entrepreneurs who enter with a type-H idea and mistakenly exit by $t = 25$. We simulate 10,000,000 entrepreneurs with over-estimation and over-precision bias while varying the number of experiments the entrepreneurs conduct to evaluate their current idea. The *conservative*, *balanced*, and *aggressive* pivot thresholds are 0.45, 0.50, and 0.55, respectively. Number of experiments (X) ranges from 1 to 20. We set $\Lambda = 1$, $\kappa_p = 0.05$, $\kappa_a = 0.01$, and $k = 153.7$.

Figure 6. Optimal pivot threshold and corresponding performance above the no pivot baseline, varying number of experiments (X) and confidence biases



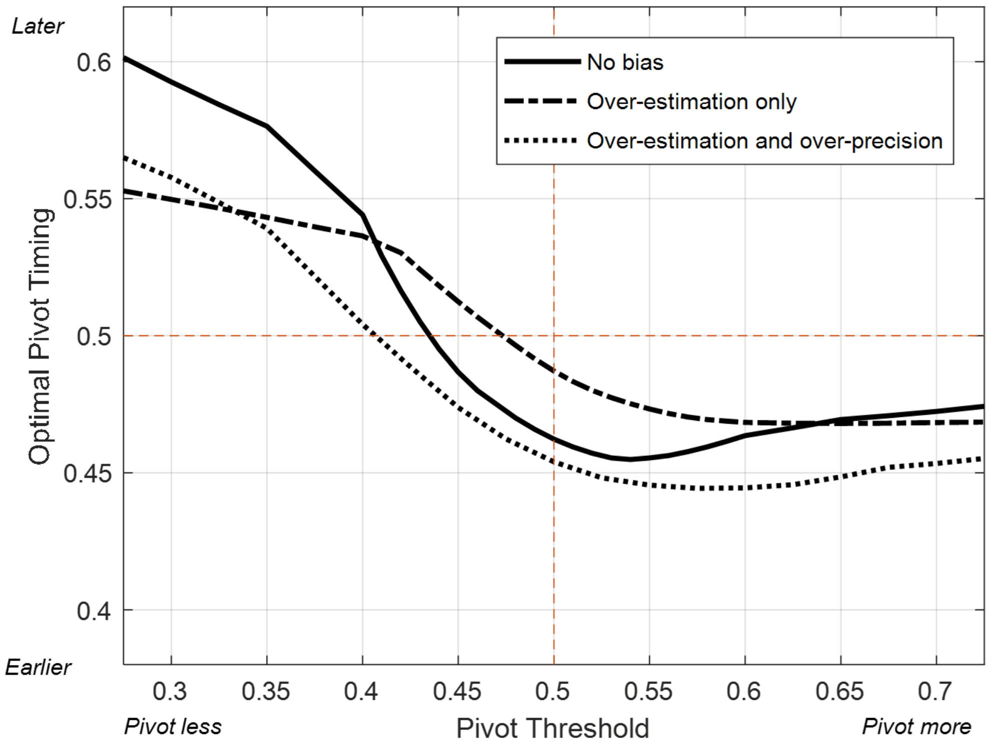
Notes: For each combination of estimation bias, precision bias, and number of experiments, we plot, in the top row, the pivot threshold that maximizes the average performance across 10,000,000 simulated entrepreneurs. For each optimal threshold, we plot, in the bottom row, the corresponding performance value in excess of that under the no-pivot strategy. We set $\Lambda = 1$, $\kappa_p = 0.05$, $\kappa_a = 0.01$, and $k = 153.7$. To simulate over-estimation and under-estimation bias, we set $\hat{p}^{init} = 0.6$ and $\hat{p}^{init} = 0.4$, respectively. To simulate over-precision and under-precision bias, we set $\hat{\tau}/\tau = 0.5$ and $\hat{\tau}/\tau = 2$, respectively. We report the no-pivot baselines for each of these combinations of biases in Online Appendix Figure C3.

Figure 7. Negative relationship between observed pivots and profitability conditional on entry



Notes: Average performance across entrants for X = 5 by number of actual pivots, pivot threshold, and confidence bias combination. For pivot strategies defined by *aggressive*, *balanced*, and *conservative* pivot thresholds with five experiments (X = 5), we plot the average profit across all entrants for 10,000,000 potentially biased simulated entrepreneurs as a function of the number of pivots taken (N). We set $\Lambda = 1$, $\kappa_p = 0.05$, $\kappa_a = 0.01$, and $k = 153.7$. To simulate over-estimation and under-estimation bias, we set $\hat{p}^{init} = 0.6$ and $\hat{p}^{init} = 0.4$, respectively. To simulate over-precision and under-precision bias, we set $\hat{\tau}/\tau = 0.5$ and $\hat{\tau}/\tau = 2$, respectively. The dotted line plots the corresponding outcome of an entrepreneur who never pivots because she conducts only one experiment with her initial idea. We omit from the plots instances of negative profits or where less than 1 percent of either entrants or total agents realizes the indicated number of pivots.

Figure 8. Optimal Pivot Timing as a Function of Pivot Policy



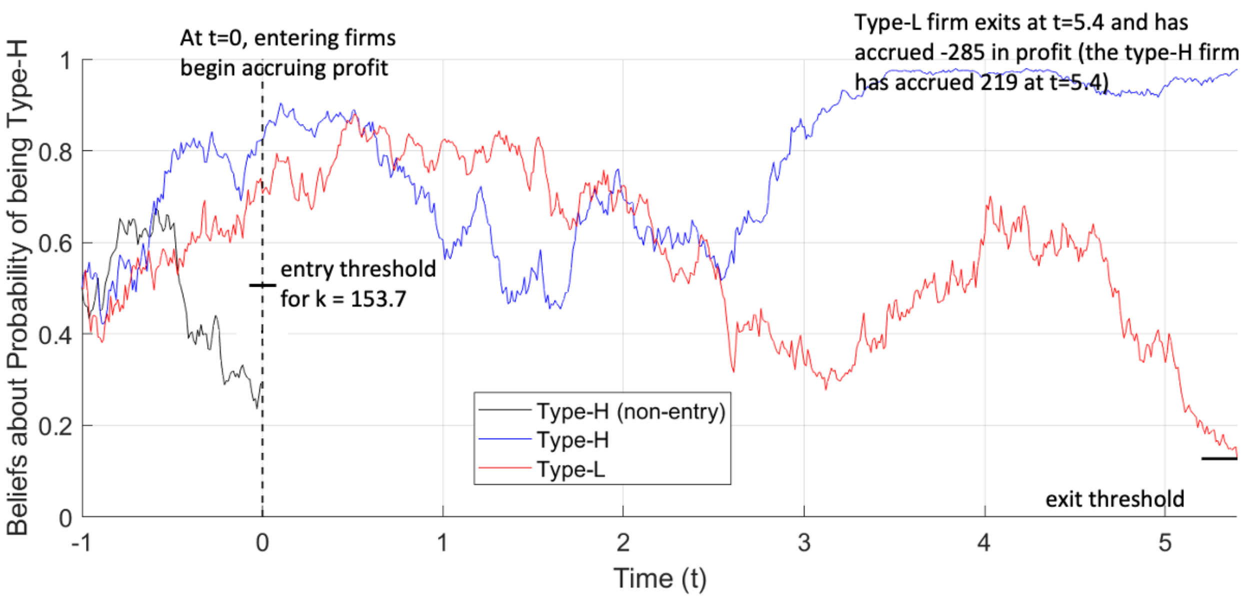
Notes: For X = 2, we plot the average performance of 50,000,000 simulated unbiased entrepreneurs for various combinations of pivot threshold and timing in order to find optimal timing as a function of pivot threshold. Here, pivot timing is the proportion of the Λ = 1 pre-entry period that is used to evaluate the first of two ideas. Pivot threshold is the belief that an agent must exceed to continue with a current idea. To simulate over-estimation bias we set $\hat{p}^{init}$ = 0.6. To simulate over-precision we set $\hat{\tau}/\tau$= 0.5.

APPENDIX A. FURTHER MODEL DETAILS

In this appendix, we provide a detailed illustration (see Figure A1) and description of the learning model of entry and exit in CCEP, as follows:

1. During the pre-entry period $t = -\Lambda$ to $t = 0$ ($\Lambda = 1$ in Figure A1), each entrepreneur receives noisy signals about potential profits, which cumulate to a summary statistic, X_t, and uses this to form beliefs about their probability of their idea being type-H, $\hat{p}_t$. No profit or loss accrues in the pre-entry period. Following Ryan and Lippman (2003, Equation 2 p. 439), with a slight adjustment for the pre-entry period, this belief is related to the cumulative profit signal as follows:
$$\hat{p}_t = \left[1 + \frac{1-p}{p} \exp\left\{-\frac{\mu_H - \mu_L}{\sigma^2}\left(X_t - \frac{\mu_H + \mu_L}{2}(t+\Lambda)\right)\right\}\right]^{-1} \quad \text{(A1)}$$
Figure A1 illustrates three representative entrepreneurs updating beliefs according to Equation A1 during the pre-entry period.
2. At $t = 0$, entrepreneurs enter if their beliefs about their idea/opportunity being type-H exceed an entry threshold that is a function of entry cost *k* (and other model parameters). In particular, Bayesian statistics can be used to deduce the minimum belief such that the entrepreneur's expected profit from entry is at least *k* (this may be derived following Ryan and Lippman's (2003) calculations, which we omit for brevity). In Figure A1, one type-H and one type-L firm enters since their beliefs exceed the threshold of 0.404, while one type-H firm mistakenly does not enter because its belief is below 0.404 at $t = 0$.
3. Firms that enter continue updating their beliefs according to Equation A1. They will exit if their beliefs fall below a threshold that is the solution to the optimal stopping problem for this model, given by Ryan and Lippman (2003, Equation 7 on p. 442). For the model parameters in Figure 3 of the main text, $p^* = 0.127$. Notice that the type-L firm exits at $t = 5.4$ in Figure A1, while the type-H firm that entered believes (correctly) that it is almost certainly type-H.

Figure A1. Beliefs over time for representative entrepreneurs



Notes: We run our simulation model with the parameters of Figure 3 and show three representative entrepreneurs, one of whom is a type-H that never enters, another of whom is a type-H that enters, and the third a type-L that enters and subsequently exits. We plot each entrepreneur's beliefs about the probability of being a type-H (i.e., $\hat{p}_t$) over time. The entry threshold is 0.5 when k = 153.7, and the exit threshold is 0.127 (and independent of k since entry cost is sunk).