THE IMPACT OF LEARNING AND OVERCONFIDENCE ON ENTREPRENEURIAL ENTRY AND EXIT

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

David C. Croson
College of Social Science
Michigan State University
profdc@msu.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

March 1, 2018

*Equal co-authors listed in alphabetical order; **Corresponding author.

Keywords: learning, opportunity assessment, bias, overconfidence, entrepreneurship

We thank seminar participants and the ESMT-Berlin, the Frankfurt School of Finance and Management, the University of Oregon, and Michigan State University; conference participants at the Academy of Management 2016, the Cambridge-Darden Entrepreneurship Conference 2016, the Center for Research on the Economics of Innovation @ Bath 2017, INFORMS 2016, the Midwest Strategy Conference 2015, and the Strategic Management Society 2015; and three anonymous referees for their helpful comments. All errors remain our own.

THE IMPACT OF LEARNING AND OVERCONFIDENCE ON ENTREPRENEURIAL ENTRY AND EXIT

ABSTRACT

Empirical evidence suggests that entrepreneurs make mistakes: too many enter markets and persist too long once there. While scholars have largely settled on behavioral bias as the cause, we suggest that this consensus is premature. These mistakes may also arise from a process in which entrepreneurs continually learn about their prospects, and make entry and exit decisions from what they have learned. We develop a computational model of this process that connects pre- and post-entry learning and can be directed to analyze fully rational or biased entrepreneurs. The model suggests that rational entrepreneurs may, to outside observers, appear overconfident, seem to take too long to exit, and exhibit a positive correlation between entry cost and persistence in the market. When examining confidence biases, the model suggests entrepreneurs whose biases cause them to perform the worst post-entry will be most likely to enter; that pre-entry learning induces a positive correlation between confidence biases among entrants, and that exit changes the prevalence of certain biases in the surviving population of entrants over time. Our study also speaks to recent work on pre-entry experience that documents the transfer of knowledge from parent to progeny firms, suggesting that, in addition to inheritance, differential performance may also be the result of heterogeneity in the length and quality of pre-entry learning during which an opportunity is assessed.

1. INTRODUCTION

Entrepreneurship is a mistake-riddled process. Entrepreneurs, by the very nature of their task, must decide whether and when to enter and exit markets based on a necessarily incomplete understanding of the merits of their opportunities. In doing so, they routinely make costly errors, manifested in two well-documented empirical patterns: *excess entry*, wherein too many nascent entrepreneurs enter the market (e.g., Camerer and Lovallo 1999; Koellinger, Minniti, and Schade 2007), and *delayed exit*, wherein entrepreneurs persist even in the face of strong evidence that they should discontinue operation (Åstebro, Jeffrey, and Adomdza 2007; Gimeno, Folta, Cooper, and Woo 1997; DeTienne, Shepherd, and De Castro 2008). The extant literature has largely settled on individual behavioral bias as the primary driver of these mistakes (Åstebro, Herz, Nanda, and Weber 2014).

In this paper, we suggest that this theoretical consensus is premature. Attributions of behavioral bias may be, in part, a consequence of theorizing, and empirically examining, entry and exit as two sequential but independent decisions. We, by contrast, examine entrepreneurial decision-making as a process of learning over time in which entrepreneurs continuously evaluate the merits of their opportunities, with pre-entry learning leading to an entry decision and post-entry learning leading, potentially, to an exit decision. In doing so, we build on the growing recognition of the importance of entrepreneurial learning activities *prior to entry* (e.g., Helfat and Lieberman 2002; Agarwal, Echambadi, Franco, and Sarkar 2004; and Klepper and Sleeper 2005; Moeen and Agarwal 2017) that are believed to have long lasting implications *subsequent to entry* (e.g., Qian, Agarwal, and Hoetker 2012). By connecting pre- and post-entry learning we demonstrate both that unbiased entrepreneurs learning under uncertainty will exhibit precisely those patterns of mistakes typically (mis-)attributed to bias, and that variations in the length and quality of the pre-entry learning period may explain, in part, post-entry decisions and performance outcomes. Additionally, we show that, while trait-like behavioral biases among entrepreneurs are not required to generate excess entry and delayed exit, overconfidence biases may produce economically important, dynamic, and surprising empirical patterns when examined within a learning model of entrepreneurial decision making.

We develop a computational model of entrepreneurial learning pre- and post-entry by Bayesian-rational and behaviorally-biased entrepreneurs. We start by assuming that a nascent entrepreneur is endowed with an opportunity (an idea). She does not know the innate quality of her idea, but knows that it may be either high-reward or low-reward. Since she knows the distribution in the population of high- versus low-reward opportunities (50/50), she has some prior beliefs. Entry into the marketplace is costly due to direct costs of entry and opportunity costs (e.g., foregone wages). Consequently, the entrepreneur seeks to learn about the merits of the idea prior to making her entry decision. For example, she may decide to work on evenings and weekends for one year in order to gather information on the quality of her opportunity (e.g., developing a prototype, talking to potential customers). This feedback is subject to myriad ambiguities that make learning difficult. At the end of the pre-entry learning period, she must decide whether to enter. This decision is premised on her subjective beliefs about future expected profits from entering, adjusted by the value of the option to subsequently exit. Post-entry, the entrepreneur will continue to learn about her opportunity by selling in the marketplace, and can choose to exit at any time if she comes to believe that her opportunity is low-reward. The model allows us to consider the decisions of entrepreneurs that are fully Bayesian rational profit maximizers. It also allows us to consider decisions by entrepreneurs that are subject to confidence biases (estimation bias and precision bias). These biases modify the entrepreneur's learning (belief updating) process, altering the pattern of entry and exit decisions.

In its application of Bayesian learning to archetypal decisions in an entrepreneurship context, our model has distinctive attributes in comparison to prior work. First, our general modeling approach provides a theoretically grounded model of learning under uncertainty, which has only rarely been applied to central questions of entrepreneurship (notable exceptions are Jovanovic 1982, and Braguinsky, Klepper, and Ohyama 2012). Second, our specific Bayesian-learning approach makes it possible to directly connect the information gained during a period of pre-entry learning with both the entry decision and later post-entry learning patterns. This is important because pre-entry learning shapes both the entry decision and the initial beliefs of entrepreneurs at the start of the post-entry period. Third, because our agent-based simulation generates a continuous assessment of each entrepreneur's beliefs, decisions,

information received, and profit history, our approach interprets what these agents are *thinking* as well as what they are *doing* at each point in time. This yields a broader set of insights for empirical researchers, who have typically used cross-sectional surveys to examine beliefs and panel data sets to examine performance, but have rarely been able to track both beliefs and performance over time. Finally, our model supports a straightforward means to incorporate confidence biases in the learning process and study their effects on critical entrepreneurial decisions. To our knowledge, ours is the first model of entrepreneurial learning to directly incorporate multiple types of bias. This enables us to shed light on the important, yet understudied, issue of how individual level bias aggregates to population level bias 'traits' of survivors post-entry (e.g., Johnson, Anderson, and Fornell 1995), an issue of broad interest to emerging work on microfoundations (e.g., Barney and Felin 2013, Aggarwal, Posen, and Workiewicz 2017); how different forms of bias interact; and how the length and quality of pre-entry learning can remedy bias.[1]

Our paper makes three distinct types of contributions to the literature on entrepreneurship and entry. First, our model of entrepreneurial learning, pre- and post-entry, provides a parsimonious unifying theoretical framework for understanding many well-known empirical regularities in entrepreneurship and management that are often considered independently. These regularities include excess entry (e.g., Camerer and Lovallo 1999; Hamilton 2000), exit delay (e.g, Elfenbein and Knott 2015), correlation between entry cost and persistence (e.g., Friedman et al. 2007; O'Brien and Folta 2009), 'optimism' among entrants (e.g., Cooper, Woo, Dunkelberg 1988), and trait-like differences between entrepreneurs and non-entrepreneurs (e.g., Busenitz and Barney 1997). In our model, these regularities result from a common underlying learning process by which entrepreneurs' beliefs about the value of their opportunities evolve. Moreover, the Bayesian-rational entrepreneurs in our model may appear, from an outside observer's perspective, to exhibit biases even though they are unbiased by construction.[2]

---

[1] We thank an anonymous reviewer for pointing out this individual/aggregate bias distinction.

[2] Students of Bayesian learning have recently begun to recognize that learning under uncertainty can lead to apparent bias. That is, an empirical researcher observing a population of agents at a particular point in time, but uninformed about the agent's full history (beliefs, information received, and choices), might observe behaviors that appear to be driven by behavioral bias even though agents are, by construction, rational. This type of observational equivalence has been the subject of recent models of Bayesian learning by Benoit and Dubra (2011), discussing "apparent overconfidence," and Van den Steen (2011), discussing "endogenously generated overconfidence." Accordingly, we argue that Bayesian learning's potential to generate apparent bias has important implications for our understanding of entrepreneurship and, in particular, our ability to evaluate the mechanisms driving empirical patterns such as excess entry and delayed exit. In their review paper, Åstebro, Herz, Nanda, and Weber (2014) are perhaps the first to note the significance of apparent overconfidence for work on entrepreneurship.

Second, our model provides a complementary perspective to strategy research on industry evolution. This work has documented the transfer of knowledge and capabilities from parent to progeny firms (e.g., Agarwal, Echambadi, Franco, and Sarkar 2004, Chen, Williams, and Agarwal 2012, Moeen and Agarwal 2017), arguing that these inheritance factors lead to observed performance differences. Our model shows that differences in survival and profitability across entrants may also be driven by the length and quality of pre-entry learning during which an opportunity is assessed. While our perspective leaves room for firm-specific variation in initial conditions of progeny firms (i.e., parental 'treatment effect'), it suggests that the role of the parent may also be related to improving the information and, hence the entry and exit decisions, of employees who are considering related entrepreneurial endeavors (i.e., a 'selection effect').

Finally, the ability of our model to move beyond purely rational Bayesian decision-making to incorporate behavioral bias, enables us to generate predictions about the types of bias that are likely to be observed in a given set of entrants, the impacts of these biases on overall patterns of entry and exit when compared with rational entrepreneurs' choices, and the profile of biases that are the most (least) harmful from a social-welfare standpoint. Further, it enables us to evaluate the degree to which longer periods of pre-entry learning can attenuate (or potentially exacerbate) the mistakes of biased entrepreneurs and to compare the value of pre-entry learning to biased and Bayesian rational agents.

2. THEORETICAL BACKGROUND

Entrepreneurship is characterized by a relatively poor distribution of financial returns (Hamilton 2000, Moskowitz and Vissing-Jorgensen 2002), a first-year failure rate approaching twenty percent (Headd, Nucci, and Boden 2010), and a ten-year failure rate exceeding seventy percent (Shane 2008). While factors that underlie these discouraging outcomes are many and varied, a central challenge for all entrepreneurs is the process of learning from feedback. For many entrepreneurs, this learning commences prior to entry, supports the entry decision, and continues post-entry to inform the continuation versus exit decision over the remainder of the venture's life (Reynolds et al. 2004; Folta et al. 2010).

In conceptualizing entrepreneurship as a process of learning, we build on foundational theoretical

accounts that conceptualize entrepreneurship as judgmental decision-making (Knight 1921, Mises 1949, Casson 1982). A core claim in these foundational accounts is that the economic viability of a nascent opportunity can be assessed only through entrepreneurial effort to form expectations of the opportunity's merits and the returns to making an investment. This decision-making is "judgmental" in the sense that such a decision is intermediate in difficulty: it is neither a simple decision which can be made via a formalizable rule nor a Herculean one in which random choice and luck dominate the effects of invested effort. Such judgment is particularly needed in entrepreneurial decision-making because entrepreneurial opportunities are "unique business investments for which it is difficult... to assign meaningful probabilities to outcomes" (Foss and Klein 2012: 78).[3]

Our premise is that the key cognitive process in entrepreneurial execution is an unfolding feedback-learning process through which an individual (or team) evaluates the merits of a given opportunity. This process starts with early diligence, prior to market entry, to gather data about the potential merits of the opportunity before substantial costs are incurred; proceeds to a critical entry/termination decision juncture where only the information gathered pre-entry is yet available; and continues (conditional on entry) with ongoing market-based feedback learning through which exit/continuation decisions are made repeatedly over time, with actual monetary consequences through business operations. This focus on ongoing learning emphasizes the improvement in entrepreneurial choices through experience, rather than a purely judgment-based view characterizing entrepreneurship as discrete decisions about entry and exit, each of which must be performed correctly but which are essentially independent of one another. While our vision of the feedback learning process does involve judgmental decision-making, it also incorporates its repeated nature as a strength – decisions generate

[3] Entrepreneurs' decisions must be undertaken on the basis of incomplete data, which itself comes from observables imperfectly correlated with entrepreneurial outcomes (Hogarth and Karelaia 2012). Prospective opportunities are frequently characterized by decision-frustrating novelty, volatility, complexity, and ambiguity (Baum, Frese, Baron, and Katz 2012, McMullen & Shepherd 2006, Politis 2005, Ravasi and Turati 2005). The most promising of these occur in emergent product markets, underpinned by unproven technologies and requiring novel management practices (Eisenhardt and Schoonhoven 1990). Given the number of factors which must continue to "go right" and are yet not under the entrepreneur's complete control, it is no wonder that many opportunities that seem initially promising eventually fail.

new feedback that is, in turn, used to update beliefs about the economic viability of the opportunity.

We are not the first to suggest that a model of learning is critical to understanding entrepreneurship. Woo, Daellenbach, and Nicholls-Nixon (1994) argue for the characterization of entrepreneurship as an ongoing process of experimentation and learning under uncertainty. Minniti and Bygrave (2001: 7) argue that a "theory of entrepreneurship requires a theory of learning." Nonetheless, "in terms of theory building, many aspects of entrepreneurial learning remain poorly understood" (Cope 2005: 373). Since extant research on learning in the context of entrepreneurship can be classified on whether learning occurs post-entry or pre-entry, with sharply limited integration between the two temporal regimes, we adopt this dichotomy in our treatment of the relevant literature, even though our model combines the two.

2.1 Post-Entry Learning

In thinking of entrepreneurship as a learning process, one is naturally drawn to the learning that takes place post-entry. Such learning can be characterized as passive or active (Pakes and Ericson 1998). Passive learning reflects an assumption that entrants are "endowed at birth with an unknown value of a time-invariant profitability parameter" and learning occurs because noisy "profit realizations contain information on the value of the parameter" (Pakes and Ericson 1998: 4). Jovanovic (1982) is the first model of passive post-entry learning in which Bayesian entrants gradually learn their ability levels (low or high), and exit if (or when) they conclude they are low ability, incurring losses until they do. Frank (1988) extends Jovanovic's model to include sunk costs and heterogeneous beliefs at the time of entry. Parker (2006: 13) empirically examines the rate at which self-employed individuals update their beliefs about their unobserved productivity, concluding that "entrepreneurs do exploit new information, but that they give much more weight to past experience than to new information when forming their expectations."

Active learning, by contrast, assumes that the entrant knows the current value of its profitability parameter, but the value "changes over time in response to the stochastic outcomes of the firm's own investments, and those of other actors in the same market" (Pakes and Ericson 1998: 4). Active learning

diverges from the judgmental decision-making approach due to its path dependence and nonstationarity. Active learning is consistent with the classic conceptualization of entrepreneurial ventures as nimble, flexible, and adaptable to their post-entry environment (e.g., Carroll, Bigelow, Seidel, and Tsai 1996) by making ongoing operational decisions that influence both present and future profitability. We note that, although passive and active learning can certainly coexist,[4] a certain amount of passive learning must occur before active-learning decisions can reasonably be claimed to be based on a known profitability parameter. For this reason, and for the sake of tractability, in modeling entrepreneurial learning, we make assumptions that are consistent with the passive learning approach. We address the limitations of this approach in the discussion section.

2.2 Pre-Entry Learning

The pre-entry activities of market entrants have become increasingly salient in the literature at the intersection of strategy and entrepreneurship. The basic claim, in literatures as diverse as ecology (Carroll, Bigelow, Seidel, Tsai 1996) and industry evolution (e.g., Klepper 2002, Agarwal and Bayus 2002), is that learning starts pre-entry (e.g., Agarwal and Moeen 2017), accrues at both the individual founder level and the firm level (e.g., Qian, Agarwal, and Hoetker 2012), and shapes the trajectory of post-entry activities. In one stream, scholars explore how contextual factors affect the knowledge and skills that prospective entrepreneurs develop through relevant work experience (e.g., Sorensen 2007, Elfenbein, Hamilton, and Zenger 2010, Sorensen and Phillips 2011, Roach and Sauermann 2015). A second stream focuses on the capabilities transferred by founders from parent firm to spin-off (e.g., Helfat and Lieberman 2002, Agarwal, Echambadi, Franco, and Sarkar 2004, Klepper and Sleeper 2005, Klepper and Thompson 2010, Chatterji 2009, Braguinsky, Klepper, and Ohyama 2012, Agarwal, Campbell, Franco, and Ganco 2016),

[4] Empirical studies have found support for both active learning and passive learning models. Pakes and Ericson (1998) find that manufacturing firms in Wisconsin exhibit empirical patterns consistent with the predictions of active learning models, while retail trade exhibits empirical patterns more consistent with passive learning models. In the US banking industry Posen and Chen (2013) find support for an active learning model in which new entrants learn to improve productivity based upon their own and others' experience, while Elfenbein and Knott (2015) find that established firms' exit behavior is consistent with a passive learning model.

in which spin-offs are born having learned routines or the identity of relationship partners that provide a productivity advantage. Yet a third stream of pre-entry learning literature examines entrepreneurs who pass through a "hybrid" period of wage employment during which they evaluate the merits of a specific commercial opportunity (e.g., Folta, Delmar, and Wennberg 2010, Burmeister-Lamp, Levesque, and Schade 2012, Raffiee and Feng 2014) and decide on when to commit to it (Croson and Minniti 2012).

Empirical examinations of the relationship between pre-entry experience and performance tend to show that such experience has a positive impact on survival and profitability although some studies find contradictory results (e.g., Dencker and Gruber 2015; Ganco and Agarwal 2009). Recent work has begun to take a more dynamic post-entry approach. For instance, Chen, Williams, and Agarwal (2012) study how *de alio* and *de novo* firms "confront impediments to growth" over time, and others study the implications for learning post-entry (Balasubramanian 2011, Dencker, Gruber, and Shah 2009).[5]

More broadly, empirical studies show that critical entrepreneurial processes begin prior to entry, a view that contrasts with earlier work characterizing entrepreneurial entry as a discrete change in managerial cognition and focus (e.g., Evans and Leighton 1989, Hamilton 2000, Van Praag and Cramer 2003). Folta, Delmar, and Wennberg (2010: 265), for instance, conclude that the "reduction of uncertainty through learning about entrepreneurial performance is an important benefit from hybrid entrepreneurship." Parker and Belghitar (2006: 98) examine nascent entrepreneurs over a one-year time horizon using data from the Panel Study of Entrepreneurial Dynamics (PSED), concluding that "for at least some of these [nascent entrepreneurs] … quitting [prior to commercialization] is a response to the realization that the business is not viable." Reynolds et al. (2004) define a gestation phase between the conception of the idea and the "birth" of the new enterprise. Using PSED data, they find that 6.2 percent of U.S. adults were engaged in trying to start new firms, with more than half of nascent entrepreneurs

[5] It is worth noting that this literature tends to consider pre-entry "experience" rather than "learning." Learning can be thought of as the outcome of experience, reflecting a better (or worse) understanding on some relevant dimension as experience is accumulated. Pre-entry experience, of course, is more amenable to empirical study as it may well be observed (i.e., work experience) and somewhat easily catalogued *ex post*.

working full-time jobs during this gestation phase – a finding corroborated in international data sets (e.g., Burke, Fitzroy, and Nolan 2008, Campbell and De Nardi 2009, Petrova 2012). Moeen and Agarwal (2017) study the incubation phase (i.e., prior to the commercialization of the first product) of the agricultural biotechnology industry, where firm investments in learning can be viewed as pre-entry (pre commercialization) experience.

These streams of research can be interpreted as suggesting that pre-entry learning activities have substantial implications, typically positive, for both the entry decision and post-entry performance and also that entry is an option shaped by pre-entry learning, rather than a foregone conclusion. Since only those who decide to become entrants actually enter, however, much of this pre-entry learning is unseen. It would be a mistake, therefore, in studies of post entry behavior and outcomes, to assume that non-entrants did not experience pre-entry learning; indeed, its lessons underlie the crucial choice to discontinue before committing (and, presumably, losing) substantial resources. A main contribution of our model lies in examining pre-entry learning, entry decisions, and post-entry decision-making as the result of a single, integrated learning process.

2.3 Errors and Bias in Learning by Entrepreneurs

Two gaps in the extant literature limit our ability to understand fully the implications of the learning processes that shape entrepreneurial decisions and outcomes.

The first is the role of behavioral bias in the *learning* process. While, over the past decade, scholars of organizations and entrepreneurship have gained a deep general understanding of the role of behavioral bias in one-shot judgemental decision-making, we know relatively little about the implications of how these biases affect the already-complicated process of learning by doing under uncertainty.

The literature on entrepreneurial learning is sometimes, at least implicitly, premised on the assumption that information acquisition is uniformly effective and, in the extreme, reflects fully rational cognitive processes leading to Bayesian belief updating (Oaksford and Chater 2009). Yet, in practice,

even unbiased entrepreneurs appear to encounter substantial information problems associated with learning from small samples (March, Sproull, and Tamuz 1991) or frustrations in making causal inferences due to unreliable feedback (March and Olsen 1975). In a recent lab experiment examining entry decisions, Artinger and Powell (2016: 1048) conclude that random errors due to uncertainty may explain as much as 60 percent of excess entry. Thus, entrepreneurs can draw incorrect inferences from experience.

The family of biases of the most specific interest to scholars of entrepreneurship are those of overconfidence, cited by many as drivers of entrepreneurial outcomes (e.g., Wu and Knott 2006, Lowe and Ziedonis 2006, Weinhardt, Petricevic, and Davis 2015, Hayward, Shepherd, and Griffin 2006, Navis and Ozbek 2016; see Åstebro et al. 2014 for a recent review noting dozens of examples over multiple decades). In a pioneering survey of 3000 entrepreneurs, Cooper, Woo, and Dunkelberg (1988) found that over half of respondents reported their own success expectations to be in excess of 90 percent, even though each believed that others had much lower success probabilities. Indeed, overconfidence has come to be viewed as a defining trait of entrepreneurs – practically a caricature. Overconfidence bias is theoretically interesting because it may impact one-shot judgemental decision making (e.g. Camerer and Lovallo 1999), but also learning (e.g., Navis and Ozbek 2016).

The cognitive psychology literature distinguishes among three forms of overconfidence (Moore and Healy 2008, Cain, Moore, and Haran 2015): (a) overestimation, where an entrepreneur would view herself to be better in some performance parameter than she actually is;[6] (b) overprecision, where an entrepreneur would be too sure she is correct about the value of some critical parameter falling in a given zone (i.e., would hold too narrow a confidence interval); and (c) overplacement, where an entrepreneur would compare herself too favorably relative to others. Not only is each form of overconfidence caused by a different underlying psychological mechanism, the degree to which each presents itself as a relevant

[6] To facilitate clarity of exposition, we will refer to overestimation as optimism and underestimation as pessimism.

and costly bias depends on the nature of the task, and they have often been confounded in the extant empirical literature (Moore and Healy 2008).[7] These varieties of overconfidence combine to create implications that differ substantially between both one another and present differently in a temporally-unfolding process of learning vis-à-vis a situation of one-shot judgemental decision-making. The challenge in examining overconfidence as a construct is that its multiple dimensions have frequently been mutually confounded or imprecisely specified.

Second, entrepreneurship research has rarely analyzed pre- and post-entry learning, and entry/exit decisions they engender, in a unified fashion. Yet there no reason to believe, even after a substantial period of pre-entry learning, that an entrepreneur has a definitive evaluation of the opportunity at the time of entry. While mistakes are discrete and large (e.g., mistaken entry), the learning process is substantially more continuous and subtle. Although any individual entrepreneurial career is naturally divided between pre- and post-entry stages, a scholarly model of it cannot be so divided without omitting a critical continuity factor that joins them: the pre-entry learning accomplished presumably carries forward to, supports decisions in, and is built upon during the post-entry stage. A prospective entrepreneur who engages in learning specific to an entrepreneurial opportunity during a pre-entry phase does not forget his/her lessons after entry, nor should she. Further, any bias that impacts an individual's learning pre-entry is not likely to disappear post-entry, nor is any bias manifest in the post-entry period likely to have spontaneously appeared.

2.4 A Model of Entrepreneurial Decision-Making

The discussion above points to a simple framework through which to understand crucial entrepreneurial decisions. To formalize this framework, we develop a computational model of entrepreneurial learning based on classic Bayesian principles that has the flexibility to accommodate either fully rational or behaviorally biased entrepreneurs. In the model, risk-neutral entrepreneurs are

[7] For example, a common approach is to ask respondents their confidence that they picked the correct answer, in which case "overestimation and over-precision are one and the same" (Moore and Healy 2008, p. 503).

endowed with business opportunities of uncertain value (i.e., profitable or unprofitable) along with initially uninformative beliefs about that value. We are agnostic about the source of these opportunities. Over time, entrepreneurs' beliefs evolve as they receive noisy signals about the value of their opportunities. Prior to entry, they study their opportunities and learn from feedback, but incur no production costs, profits or losses. Conditional on their beliefs about the value of their opportunities, they make profit-maximizing decisions at the end of a pre-entry learning period, choosing entry or abandonment; during the post-entry period they learn from realized profits and losses and continuously choose continuation versus exit. While all agents in our model maximize profits conditional on their beliefs, two types of bias can be introduced into the belief-formation process in the model: estimation bias in the form of biased beliefs at the outset of the pre-entry learning process and confidence bias in the form of biased belief updating. These biases may affect agents' decisions in important ways. We preview the model, its main mechanisms, and principal results in Figure 1.

<<INSERT FIGURE 1 HERE>>

3. COMPUTATIONAL MODEL

We now detail a simulation model in which agents learn in two stages (pre- and post-entry) about their likelihood of eventual success. We use the term "nascent entrepreneur" to refer to all agents prior to the entry decision (i.e., the full population of agents in our model); "entrants" refers to agents who enter after the pre-entry period. Pre-entry learning shapes the nascent entrepreneur's entry decision, functioning as an endogenous selection mechanism that generates the distribution of nascent entrepreneurs' beliefs about their potential venture's prospects and encourages them to make an initial entry investment (or discourages them from doing so). Post-entry learning supports the continuation and exit decisions of those who decide to enter. We begin by detailing the structure of the model. We then proceed to show how pre-entry learning impacts the distribution of nascent entrepreneurs' beliefs immediately prior to the entry decision, which drives many of the critical outcomes of the model.

3.1 Model Structure

We construct our simulation starting from Ryan and Lippman's (2003) model of optimal exit from a project with noisy returns. In this model, a manager must make a decision to continue or shut down an ongoing project of unknown quality based on noisy performance information. The Ryan and Lippman (henceforth RL) model can be thought of as a restricted one-armed bandit model (e.g., Gittins 1989; Posen and Levinthal 2012) that is amenable to closed-form solutions for both the manager's optimal stopping rule and the value of the opportunity conditional on following it, given any set of beliefs.[8] The critical addition we make to the RL model is to incorporate a period of pre-entry learning that forms the basis for an initial entry decision, in which agents decide whether the opportunity's value exceeds the entry cost. We consider the entry cost to include, in addition to a potential explicit cost initially committed to the venture, the opportunity cost associated with, for example, forgone wages from leaving paid employment if the agent were to choose to launch a business after the pre-entry learning period. Thus, during the pre-entry learning phase, nascent entrepreneurs focus on assessing the value of their opportunity and, conditional on the decision to enter, plan to make continuation/exit decisions during the post-entry learning phase.

Following the RL model, a nascent entrepreneur is initially randomly allocated either a profitable or an unprofitable opportunity. The profitability of each opportunity is characterized by its profit rate: the average amount that will be earned each period. With probability *p*, the opportunity is profitable (type-H) with an underlying mean profit rate $\mu_H > 0$. With complementary probability $1 - p$ the opportunity is unprofitable (type-L) with an underlying mean profit rate $\mu_L < 0$. An entrepreneur of type-H (type-L) would observe a payoff signal drawn from a normal distribution with mean μ_H (μ_L) and variance σ^2. Although the nascent entrepreneur is not endowed with the knowledge of the true quality of her particular opportunity, she knows the values of μ_H and μ_L and the noise component, σ^2, associated with the profit

[8] While many aspects of multi-armed bandit models, including optimization routines and the probability distributions resulting from optimal decisions (see, e.g., Gittins 1989) have become well-characterized in the statistics literature, closed-form solutions for the value of optimal future play conditional on knowing a set of historical outcomes are generally available only under very restrictive conditions.

signals she will receive both before and after entry.[9] Given these assumptions (and continued participation in the market), cumulative profit signals, X_t, exhibit Brownian motion with drift μ and variance σ^2.

In keeping with the core idea that knowledge acquisition and learning occur both pre- and post-entry, the nascent entrepreneur, although uncertain about whether her particular opportunity is profitable (i.e., type-H), begins with a belief on the likelihood of her opportunity being type-H. She then continuously updates her beliefs as she receives signals of profitability. In particular, an agent's beliefs at time t about her opportunity's type are fully described by $\hat{p}_t$, which is her perceived probability that the opportunity is type-H, and where $1 - \hat{p}_t$ is the perceived probability the opportunity is type-L. These beliefs, based both on the initial prior and experience accumulated, are updated as an agent learns from experience; at any given point in time, t, each agent can form a posterior probability $\hat{p}_t$ that her opportunity is type-H. Agents in the model discount future profits at rate $\delta > 0$ and make profit-maximizing decisions conditional on their beliefs.[10]

Ryan and Lippman demonstrate that $\hat{p}_t$ is a function of cumulative profit signals (X_t), signal volatility (σ^2), profit rates in each state (μ_H and μ_L), and the *ex ante* probability of being type-H (p), but is independent of the specific pattern (i.e., order) of profit realizations. Accordingly, it is optimal to exit when $\hat{p}_t$ first falls below a critical threshold p^*, which is a function of p, μ_L, μ_H, σ^2, and δ and thus known to the entrepreneur from the outset. The option to abandon is fully incorporated in the RL formulation, and agents will persist even when their expected returns from operating indefinitely are below zero.

We extend the RL model to incorporate the nascent entrepreneur's period of pre-entry learning and the subsequent entry decision. Rather than agents beginning to receive information only at the time of entry (time 0 in RL), we assume that nascent entrepreneurs begin learning about the opportunity prior to entry and choose to enter only if they believe the expected value of doing so, net of entry's opportunity

[9] For simplicity, we assume in our main analysis that the pre- and post-entry signal-to-noise ratios are identical. This assumption, however, is not critical to any of our results, and we discuss below what happens when this assumption is relaxed.

[10] Thus, we abstract in the core model from social or psychological factors that might affect decision-making conditional on beliefs (*e.g.*, a stigma associated with failure), attitudes towards risk, or non-pecuniary private benefits associated with entrepreneurship which might ordinarily be captured by modeling entrepreneurial utility rather than profit (as in Croson and Minniti 2012).

cost, is positive. More specifically, agents' beliefs evolve during a pre-entry learning period of length **Λ** (*i.e.*, from t = **-Λ** to 0). In the pre-entry period, their cumulative signals, X_t^{pre}, accrue costlessly, and are not associated with any profit or loss. Conceptually, these signals come from, but are not limited to, activities such as market research, soliciting feedback on business plans, seeking out and evaluating potential suppliers, and visiting competitors. Post entry, agents receive the both the information signals and actual profits and losses based; we designate the accrued signals and profits post-entry as X_t^{post}.[11]

We define the initial belief held by an agent as $\hat{p}_{-\Lambda}$ and the belief that comes to be held at the critical time $t = 0$ at which the entry decision must be made as $\hat{p}_0$. A crucial implication of modeling pre-entry learning and entry is that $\hat{p}_0$ is a stochastic outcome of accumulated profit signals in the pre-entry learning period and will vary across agents (in contrast to the RL model, where all agents hold identical entry beliefs of $\hat{p}_0 \equiv p$). At $t = 0$, each agent must make a decision of whether to enter or to forego the opportunity. In the RL model, there is a one-to-one correspondence between beliefs and the expected value of the opportunity, conditional on optimally exercising the option to cut losses by exiting. In our simulation, the agent assesses this expected value at $t = 0$ (a direct function of its belief $\hat{p}_0$) and enters if and only if the expected value exceeds *k,* the opportunity cost of entry. Figure 2 illustrates the timing of the model, and demonstrates how decisions made by type-L and type-H agents in the simulation separate them into different sub-populations over time.

<<INSERT FIGURE 2 HERE>>

Given this model structure and the nature of belief updating, we further extend the RL model to incorporate two forms of behavioral bias associated with over- or under-confidence. First, we define *over-* or *under-estimation* as bias in initial beliefs (i.e., at the start of the pre-entry learning period, $t = -\Lambda$) which may reflect either over-estimation (optimism) or under-estimation (pessimism) about the probability the opportunity is type-H. Estimation bias is modeled by setting the agent's initial belief $\hat{p}_{-\Lambda}$ to be different from (higher or lower than, respectively) the true probability, *p*, that the opportunity is

[11] One might imagine that pre-entry signals may differ from those post-entry signals, e.g., pre-entry signals may be noisier. Higher signal noise, however, is observationally equivalent to a shorter pre-entry learning period, which we demonstrate in section 3.2 below. Therefore, for parsimony, we refer to the stochastic characteristics of X_t^{pre} and X_t^{post} as identical in describing the model.

type-H. When $\hat{p}_{-\Lambda} > p$, agents are optimistic. Second, we define *over-* or *under-precision* as biased beliefs about the precision (noisiness) of profit signals. This determines whether the agent will update her beliefs too slowly or too rapidly relative to the optimal (Bayesian) rate of belief updating. Per standard convention, we define precision, τ, as the inverse of variance in profit signals (*i.e.*, $\tau = 1/\sigma^2$) and designate the agent's perceived precision parameter as $\hat{\tau}$. When $\hat{\tau} < \tau$, agents believe that profit signals are less informative than Bayes' Rule would indicate and consequently exhibit over-precision, updating their beliefs about the probability of being type-H more slowly than would a Bayesian learner.

We exercise the model computationally fixing $p = 0.5$, $\mu_L = -50$, $\mu_H = +50$, $\sigma = 100$, and $\delta = 0.1$, while varying, k, $\mathbf{\Lambda}$, $\hat{p}_{-\Lambda}$, and $\hat{\tau}$.[12] While some of our directional results could be obtained with an analytical model, our computational approach allows us to completely characterize the implications of different behavioral assumptions at every point in time, *i.e.*, we can compute the beliefs, profits, and entry/exit decisions of all agents, both in aggregate and individually, as functions of the information they have received. This complete access to agent-specific information enables us to study the timing of agents' exit, which cannot be readily derived in closed-form within optimal stopping models, and to evaluate how the beliefs and traits of surviving populations change dynamically over time. Most critically, such a computational approach enables us to isolate the impact of over/underconfidence biases and identify their empirical footprints separately from other confounding factors.

In exercising the model, we focus on a number of critical measures of entrepreneurial performance. Given that p, μ_L, μ_H and δ are fixed, performance is determined by cost and incidence of three types of errors: (I) low types that mistakenly enter and persist, (II) high types that mistakenly fail to enter at all, and (III) high types that enter, but subsequently exit mistakenly. Since low types that enter both pay the entry cost and accumulated losses as long as they stay in the market, the cost of error (I) is a function of both k and how long it takes low-type entrants to exit the market given that they entered incorrectly. The cost of error (II) represents the forgone stream of earnings from an opportunity that would have

[12] At these parameter values, an agent with correct initial beliefs and no pre-entry learning who is constrained to operate indefinitely will be indifferent between entry and non-entry at k = 0, since the expected value of operating indefinitely is $[p\mu_H+(1-p)\mu_L]/\delta$. The option to cut losses, which is a fundamental component of the RL model, has a value of 153.7 under these parameter values, and is independent of the entry cost.

succeeded, and is thus characterized by the unrealized perpetuity value of the high type, μ_H / δ less the entry cost *k*. The cost of error (III) can be characterized the same way as error (II), treating the entry cost as sunk and starting from the time the agent erroneously exits. The right panel of Figure 2 shows the impact on the incidence of errors made by type-L and type-H agents resulting from individual increases in *k*, $\mathbf{\Lambda}$, $\hat{p}_{-\Lambda}$, and $\hat{\tau}^{-1}$ holding the other parameters fixed.

We focus on five output measures from the model. (1) *Beliefs of entrants*. The agents' beliefs that their opportunity is type-H. This can be assessed at any point in the simulation, and is particularly informative immediately pre or post the entry decision. (2) *Entry rates of high types and low types*. Taken together, the entry by the two types define the overall entry rate, which can be compared to the case of no pre-entry learning, $\mathbf{\Lambda} = 0$. Entry by low types and mistaken failure to enter by high types determines the failure rate in each simulation. (3) *Time to exit for failed enterprises*. To capture the notion of delayed exit, we define this measure as the average time required for type-L firms to exit.[13] (4) *Gross profit per entrant.* We report the aggregate discounted flow of post-entry operating profits divided by the number of actual entrants. This mean profit rate is a function of the ratio of type-H to type-L entrants and properly ignores entry cost. Such a measure corresponds to the accounting returns an econometrician would observe when analyzing the performance of a population of actual entrants. (5) *Net profit per agent*. We report the aggregate discounted net flow of post-entry operating profits divided by the number of agents in the simulation. This net profit metric differs from the gross profit metric in two ways: it reduces profits by entry costs and it averages across all agents who begin the pre-entry learning process (including those that do not enter). The net profit of all agents in the simulation provides a measure of the social welfare created by entrepreneurship in the model; absent entrepreneurship, these gains would not be realized.[14]

3.2 Characterizing the Distribution of Beliefs Immediately Prior to the Entry Decision

Before proceeding to the main results of the model in Section 4, we briefly describe the implications of pre-entry learning for entrepreneurs' beliefs immediately prior to the entry decision. We do so by

[13] Some type-H firms do mistakenly exit; however, the proportion of total exits by type-H firms is small and has no qualitative effect on time-to-exit results.
[14] We abstract away from calculating consumer surplus, which is left as a potential future extension.

plotting the distribution of beliefs at the end of the pre-entry learning period, $\hat{p}_0$, for different durations of the pre-entry learning period, **Λ**, and different levels of noise in the feedback signal pre entry, σ. We assume in this section that entrepreneurs start with unbiased initial beliefs and update these beliefs accurately – assumptions we later relax.

A central feature of the model is that as the population of agents receive information during the pre-entry learning period, their beliefs immediately prior to the entry decision, $\hat{p}_0$, diverge to form a distribution. Recall that we provide entrepreneurs with initial beliefs about their opportunities at the start of the pre entry learning period. For unbiased agents, we set $\hat{p}_{-\Lambda} = p = 0.5$, i.e., the initial distribution is degenerate with all agents believing that they are equally likely to be type-H or type-L. In Figure 3, Panel A, we examine pre-entry periods of three different lengths, **Λ**=0.5, 2, and 5. The leftmost part of the panel shows the aggregate beliefs of all entrepreneurs, while two adjacent panels decomposes results between high and low types. A short period of pre-entry learning, **Λ**=0.5, has a moderate impact on beliefs, leading to a normal-ish distribution around 0.5. Yet these beliefs do little to inform entrepreneurs of their true type; this brief pre-entry learning period has a significant likelihood of misleading agents (i.e., some type-L agents may receive information that is consistent with a greater likelihood of being type-H, and thus be predisposed to enter when they should not). A longer pre-entry period, conversely, has a greater impact on shifting the distribution of agents' beliefs.

The distribution of beliefs immediately prior to entry has important implications for the entry decision. In particular, agents' beliefs at $t = 0$ interact with the entry cost to generate the patterns of entry. Each value of k in the figure, as discussed in section 3.1, defines a threshold level of beliefs at the end of the pre-entry learning period, above which the agent enters and below which she does not. Because entrants with low expectations of success do not enter, this left-side truncation defines the distribution of entrants' beliefs immediately post entry.

<<INSERT FIGURE 3 HERE>>

Analogously, we can hold the length of the pre-entry period fixed (e.g., **Λ** = 2) and vary noise ratio pre- to post-entry noise from 0.5, 1, and 2 (i.e., pre-entry noise may be twice that of post-entry noise). We

do so in Panel B of Figure 3. As the graphical depiction of this alternative modeling approach shows, it is the total amount of information collected that determines the shape of the belief distribution immediately prior to the entry decision. A shorter pre-entry period with more informative (less noisy) data per period leads to the same accumulation of evidence for (or against) entry as does a longer pre-entry period but with less information per period. For simplicity, we hold pre-entry noise fixed and vary $\mathbf{\Lambda}$ in the analysis reported below. Increases (decreases) in $\mathbf{\Lambda}$ may be appropriately interpreted as more (less) informative pre-entry learning.

4. RESULTS

We proceed to examine five questions in our analysis. First, we examine the impact of pre-entry learning on the pattern of entry and exit decisions, and profitability for Bayesian rational agents. Second, we examine the implications of estimation and precision bias for outcomes. Third, we consider the extent to which pre-entry learning can compensate for bias. Fourth, we examine the impact of endogenous selection processes when there is distribution of bias in the population, such that, on average, agents are unbiased. Finally, we examine a population of agents drawn from a symmetric distribution of both estimation and precision biases, such that, on average, agents are unbiased. In doing so, we examine how selection (entry and exit decisions) impacts the distribution of biases among entrants, and how these distributions change over time as the result of exit. In our discussion, we refer to nascent entrepreneurs, those that start the pre-entry learning process, as "agents," and those that choose to enter the industry by investing at the end of the pre-entry learning period as "entrants."

4.1 Impact of Learning Quality and Entry Cost on Entry, Exit, and Performance of Unbiased Agents

We begin our analysis by establishing a baseline properties of the model for rational agents – they form beliefs about the likelihood of success and update these beliefs, according to Bayes Rule, conditional on the performance information they receive. Figure 4 summarizes the simulation results as a function of the length of the pre-entry learning period, $\mathbf{\Lambda} \in [0, 5]$, and the entry cost, $k \in [0, 200]$.[15] We examine entry rates, beliefs, observed failure time, gross profits per entrant; and net profit per agent.

[15] For type-H agents, the gross value of entry equals $\mu H/\delta = 500$.

<<INSERT FIGURE 4 HERE>>

We summarize the key results from Figure 4 in advance of a more detailed discussion. Our model unifies several well-known empirical patterns through a single (pre- and post-entry) learning mechanism. These patterns would be seen by an observer of the post-entry context as potentially reflecting bias, but requires neither behavioral biases nor the evolution of capabilities. First, entrants' beliefs about their prospects for success will evolve pre-entry such that amongst those that enter, the average belief about the probability of success far exceeds the expected probability of success at the outset of the learning process. Second, higher entry costs are associated with later exit. This suggests a correlation between sunk costs and delayed exit, and to the extent that entry costs reflect individual-specific opportunity costs, higher ability agents are more likely to survive conditional on entry. These first two results suggest that learning pre- and post-entry, along with endogenous entry and exit decisions, may lead to "observed bias" – an econometrician observing the set of entrants may infer bias even in its absence. Third, longer pre-entry learning is associated with higher post-entry profits and survival. We next turn to the detailed discussion of the results.

In panels A and B, we display entry rates for low and high-type agents, respectively. At $\mathbf{\Lambda} = 0$ (i.e., no pre-entry learning), all agents enter for $k < 153.7$. The fact that agents who believe that the odds of success are 50-50 enter even at a substantial cost reflects the option value of abandonment in the RL model. When the pre-entry period is short, i.e., low $\mathbf{\Lambda}$, low-type agents begin to be deterred from entering. This entry deterrence effect grows stronger as $\mathbf{\Lambda}$ increases and as entry cost k increases. Entry by high types is also deterred when the pre-entry period is short. For these high-types, a little bit of pre-entry learning can be a dangerous thing – a short pre-entry period gives high type agents an opportunity to err because they receive a noisy signal that erroneously points to poor performance from a high-type opportunity. As $\mathbf{\Lambda}$ increases, the entry patterns between the two types of agents diverge: low-types (correctly) enter at ever lower rates, whereas high-types (correctly) enter at ever higher rates. These patterns are magnified as entry costs, k, increase.

Panel C displays, for the subset of agents that enter, average beliefs about the success probability at $t = 0$ (immediately post entry) for various levels of k and $\mathbf{\Lambda}$. Entrants' beliefs show both a "weeding out"

and a "seeding in" effect on low- and high-types, respectively. Observed beliefs increase in $\mathbf{\Lambda}$, because the longer learning opportunity increases the accuracy of beliefs such that low-types are less likely to enter mistakenly (weeding out) and high-types are more likely to enter (seeding in). These observed beliefs also increase in k, which is the hurdle that expected profits must clear if entry is to be profitable. Furthermore, high-type entrants have even higher beliefs about their likelihood of success as $\mathbf{\Lambda}$ grows.

This process of endogenous selection based on beliefs leads to the pattern of time-to-exit for low-types displayed in Panel D. At all levels of $\mathbf{\Lambda} > 0$, low-type entrants time-to-exit is increasing in k. This occurs even though agents in our model are unbiased (and per our discussion in the model setup, the value of the option to abandon is independent of k). Thus, our model produces a rational Bayesian explanation for the link between sunk cost and persistence that is often attributed to the psychological phenomenon of escalation of commitment (Staw 1981) or sunk cost bias (Garland 1990). Somewhat paradoxically, for $k > \sim 50$, exposure to more pre-entry information leads, on balance, to *longer* exit delays. This unusual effect occurs because as k increases, only those increasingly rare low-types who received a sufficiently long series of misleading positive signals will enter in the first place, and thus require a long period of post-entry unprofitability to correct their beliefs. In low opportunity cost settings, i.e., for $k < 50$, time to exit is a non-monotonic function of $\mathbf{\Lambda}$, reflecting early post-entry learning as continued experimentation to determine venture viability.

We next turn to the simulation's illustration of the relationship among pre-entry learning, the opportunity cost of entry, and long-term profitability. Panel E reports the average gross profitability of entrants (excluding entry cost k) as a function of k and $\mathbf{\Lambda}$. Researchers seeking to understand the relationship between entrant characteristics and performance have typically focused on measures such as profitability and growth, along with the quality of preparation for entry. In this tradition, panel E demonstrates a clear relationship between profitability and $\mathbf{\Lambda}$: the longer the period of pre-entry learning, the greater the average profitability of entrants. Since agents in our model do not improve their capabilities over time, this relationship is driven purely by selection: increased quality of pre-entry information causes the ratio of high- to low-type entrants to increase as high types are seeded in and low types are weeded out. Although much of the literature has focused on the development of capabilities

prior to entry as the main determinants of post-entry success (e.g., Helfat and Lieberman 2002), an alternative possibility – illustrated by this model – is that differences in quality and quantity of pre-entry information about the opportunity can drive systematic differences in post-entry performance. For example, *de alio* entrants, having experience in an adjacent market, may have superior information about the quality of a new business opportunity than *de novo* entrants who, by definition, have no such information, and as such, *de alio* entrants make better entry decisions.

A further, straightforward, implication comes from examining Panel E's evidence about opportunity cost. Insofar as opportunity cost k is positively correlated with an underlying meritorious attribute specific to agents (e.g., ability, or the likelihood of receiving a promotion or outside offer when remaining in paid employment), then we would observe a positive relationship between such ability and average performance post-entry. As above, in our model this relationship cannot be a result of high-ability agents' extra capability to exploit entrepreneurial opportunities; rather, their improved performance occurs because their belief threshold for entering is higher because of their better outside alternatives.

Finally, we turn to the total net profitability of all agents in the simulation, i.e., total returns to both entrants and non-entrants, net of entry cost. This measure may be interpreted as proportional to the expected profitability of a agent, a nascent entrepreneur, who begins the process of learning about an opportunity (i.e., the value of the option to pursue or abandon entrepreneurship) or, alternatively, as an absolute measure of the total cohort-wide profits generated by the entrepreneurial process we model. We expect that policy makers and managers should focus on this measure since it captures the social opportunity cost of excess entry (per von Weisacker 1980; Mankiw and Whinston 1986; Camerer and Lovallo 1999). Panel F displays how total net profits change as a function of k and $\mathbf{\Lambda}$. Unsurprisingly, expected net profits increase with the quality of pre-entry learning and decrease with k. Although for high types a little bit of learning, as noted above, is more harmful than none at all (cf. Panel B), this initial learning deters entry by low types at a greater rate, leading to a positive net effect. Similarly, although higher levels of k reduce low-type entry more than high-type entry, the net effect of an increase in k is still negative because this cost must be paid by every agent that enters. Panel F also shows that the expected return to each incremental unit of learning is higher as k increases. Thus, additional data from longer $\mathbf{\Lambda}$,

and higher cost of entry k, complement one another in deterring low types from entering.

These findings, taken together, are noteworthy. While many of the results from the model have familiar analogues in the extant literature, each is typically explained by separate and distinct theoretical mechanisms, sometimes rational (e.g., delayed exit as a function of option value) and at other times behavioral (e.g., excess entry as a function of overconfidence). In contrast, our parsimonious model of learning pre- and post-entry with endogenous entry and exit decisions, produces many of the empirical patterns observed in the extant literature all within a rational framework. For example, the association between entry cost and exit delay is often attributed to organizational and psychological mechanisms labeled as escalation of commitment. The relationship among survival, profitability, and "parental origin" of entrants (e.g., spinoffs from the same industry vs. spinoffs from different industries) is typically attributed to the transfer of capabilities from parent to progeny, i.e., technology, routines, or knowledge that lead to a higher *ex ante* probability of success. Our model, by contrast, demonstrates that the same patterns can be generated, for example, if within-industry spinoffs have equal *ex ante* probabilities of success, but are more accurate at assessing technological opportunities because of their superior pre-entry information. Finally, the positive correlation between ability in paid employment (i.e., opportunity cost) and entrepreneurial success is often interpreted as meaning that skill in paid employment is correlated with skill in entrepreneurship. While our model does not invalidate this inference, it suggests that some of this positive correlation may come from the fact that those with high opportunity costs have an incentive to be significantly more selective about the entrepreneurial opportunities they pursue, leading to an overall higher rate of success for those who overcome this hurdle. This result is similar in spirit to that of Astebro, Chen, and Thompson (2011), whose model develops a positive correlation between entry cost and self-employment wages due to self-selection.

4.2 Impact of Bias on Entry, Exit, and Performance

Having established a baseline for the behavior of unbiased agents, we extend the computational model to include two types of bias especially common in the entrepreneurship literature. First, we examine agents' estimation bias in their initial beliefs about the likelihood of having a high-profit

opportunity. In particular, we model the impact of *estimation bias* in that initial beliefs that are either *optimistic* (over-estimation: believing that the *ex ante* probability of success is greater than 0.5) or *pessimistic* (under-estimation: believing that the *ex ante* probability of success is lower than 0.5). Second, we examine *precision bias* of these beliefs such that the process of learning (i.e., belief updating) is non-Bayesian in a specific way. In particular, beliefs may be *under-precise* (updating to rapidly to new information) or *over-precise* (updating too slowly) relative to those of a Bayesian learner. Our main results come from examining the interaction of these two forms of bias with pre-entry learning.

In the results in Figure 4, we hold the pre-entry learning period and entry costs fixed, at $\mathbf{\Lambda} = 1$ and $k = 100$, respectively, and examine how the two forms of bias affect outcomes, both separately and together. We consider outcomes including entry rates, the time needed for low-type entrants to exit, average gross profit per entrant, and the net profit per agent. The unbiased agent has neutral precision of $\hat{p}_{-1} = 1$ (y-axis) and neutral estimation of $\hat{\tau} = 0.5$ (x-axis).

<<INSERT FIGURE 5 HERE>>

Several noteworthy patterns emerge. First, *entry rates are highest among exactly those nascent entrepreneurs whose average profits, conditional on entry, are lowest* (see the bottom-right corner of Figure 5, Panel A and Panel C). These agents are endowed with both initial optimism, overestimating *ex ante* the likelihood of being high-type, and over-precise, updating beliefs too slowly when faced with new information. The mechanisms driving the extremely poor profitability for these agents are clear: too many enter despite their low-profit prospects and they persist too long in the market conditional on entry (per Panel B). As a group, then, these agents perform poorly (as shown in the bottom-right corner of Panel D). Agents who start with extremely pessimistic beliefs and also suffer from over-precision perform as poorly (bottom left corner of Panel D), but for the opposite reason. Entry by these pessimistic, over-precise agents is very rare. Few low-types actually enter, so the average gross profitability per entrant in Panel C is very high because the profitability contribution of high-types is not diluted by the entry of low-types. Nevertheless, as shown in Panel D, net profitability for pessimistic, over-precise agents is very low, because many high-types with these biases mistakenly choose not to enter. Over-precision is thus

identified as being particularly harmful.

A second set of patterns is equally striking: agents with neutral-to-modest over-estimation ($\hat{p}_{-1}$ in the neighborhood of 0.5 - 0.6) and under-precision *perform nearly as well as fully unbiased agents* (see the central contour of Figure 5 Panel D). The central contour in Panel D reflects the fact that under-precision has very little cost for agents with correct initial beliefs or who possess modest initial optimism, in contrast to the heavy cost of over-precision. More generally, agents who begin the learning process with optimism (over-estimation of 0.8), but update beliefs twice as rapidly as the unbiased agent (under-precise at 2), generate expected profits that are within 10% of the maximum. These agents are more likely than unbiased agents to enter (both high- and low-types), but low-types cut their losses quickly when they enter with a low-profit opportunity (per Panel B upper right corner).[16] Thus, optimism is partly offset by under-precision bias, which may reflect the logic in the entrepreneurial mantra of "fail fast, fail often."

4.3 Pre-Entry Learning as a Means of Compensating for Bias

Gathering more (or better) information during the pre-entry period should improve an agent's expected performance and has the potential, over time, to "correct" for biases in both estimation (initial beliefs) and precision. To examine this possibility, we explore how extending the pre-entry period impacts the net profits of agents (entrants and non-entrants) across a spectrum of biases. Figure 5 compares the performance of agents with pairwise combinations of initial beliefs ($\hat{p}_{-\Lambda}$ = 0.25 and 0.75) and effective precision ($\hat{\tau}$ = 0.5, 1, and 2).

<<INSERT FIGURE 6 HERE>>

Extending the pre-entry learning period generally improves the expected profits for agents with nearly any profile of biases.[17] The magnitude of impact, however, differs substantially for agents with different combinations of bias. Under many bias settings, net profit per agent approach the fully Bayesian (unbiased) benchmark level of performance as $\boldsymbol{\Lambda}$ becomes sufficiently long. Consistent with Figure 5,

[16] High-type agents with optimism and under-precision are less likely to fail to enter (*i.e.*, they avoid this mistake), but are more likely to mistakenly exit following entry. While one type of mistake is more frequent, the other is less frequent, and the effects roughly balance each other out.

[17] We do observe one exception to this statement: pessimistic agents going from $\boldsymbol{\Lambda}$ = 0 to $\boldsymbol{\Lambda}$ = 0.25 exhibit a small decrease in expected profits.

Panel D, *optimistic, under-precise* agents ($\hat{p}_{-\Lambda}$ = 0.75, $\hat{\tau}$ = 2) agents perform nearly as well as their Bayesian counterparts for all values of **Λ**. By contrast, *pessimistic, under-precise* agents ($\hat{p}_{-\Lambda}$ = 0.25, $\hat{\tau}$ = 2) underperform substantially – paying heavily for their bias – when the pre-entry learning period is short (i.e., when **Λ** < 1), but exhibit high marginal benefits from additional pre-entry experience and steadily approach the Bayesian rational benchmark as **Λ** increases. For both *pessimistic* and *optimistic, over-precise* agents ($\hat{p}_{-\Lambda}$ = 0.25, $\hat{\tau}$ = 0.5 and $\hat{p}_{-\Lambda}$ = 0.75, $\hat{\tau}$ = 0.5, respectively), similarly small amounts of pre-entry learning do little to alleviate the penalty related to bias. For both types of over-precise agents, however, the marginal benefit of additional pre-entry learning *increases* until **Λ** = 2.[18]

As Figure 6 indicates, over-precision biases are much more difficult to correct via additional learning than under-precision biases. The speed at which learning corrects under-precision bias depends on whether it is combined with estimation bias and, if so, the degree of bias (regardless of whether it is optimistic or pessimistic). Given either over- or under-estimation in initial beliefs, under-precise agents ($\hat{\tau}$ = 2) outperform agents with correct precision ($\hat{\tau}$ = 1) for all values of **Λ**.

Together the analyses in Figures 5 and 6 shed light on the "fail fast, fail often" mantra that has become widespread in hotbeds of innovation such as Silicon Valley (Babineaux and Krumboltz 2013). On the one hand, agents who start the pre-entry learning process with optimistic beliefs, but overreact to new information because of under-precision, perform nearly as well as those who are completely unbiased. On the other hand, these types will still benefit significantly from spending additional time learning before committing to an entry decision. Their marginal returns to pre-entry learning are comparable to, and can even exceed, the returns to learning by unbiased agents.

Figure 6 also provides a detailed answer to a seemingly simple, but remarkably complex, question: is it preferable for entrepreneurs to be optimistic or pessimistic? The answer is that *it depends on both the extent of pre-entry learning and an agent's precision bias*. Given a short period of pre-entry learning (**Λ** < 1), it is more profitable to be optimistic, irrespective of precision bias; similarly, it is better to be under-precise than over-precise regardless of one's estimation bias. Interestingly, with longer periods of

[18] Additionally, it is worth noting that, when combined with either over- or under-estimation, under-precision performs better than accurate Bayesian updating.

pre-entry learning, over-precise agents are better off if they begin as pessimists rather than as optimistics. For over-precise agents, a long pre-entry learning period eventually enables pessimists to outperform optimists by "seeding in" the high type agents while continuing to "weed out" the low type agents.

4.4 Pre-entry Learning, Selection, and the Cost of Bias

We next consider a context in which the population of agents that begins the pre-entry learning process exhibits a distribution of estimation and precision biases, but biases are uncorrelated and the median agent has no bias *ex ante*. We analyze how pre-entry learning impacts the selection of entrants and overall performance of agents. We begin by setting k = 100 and comparing the average net profit per agent for multiple values of $\mathbf{\Lambda}$. We do so across four different populations: (P1) agents that are Bayesian rational with correct estimation of initial beliefs and precision, i.e., $\hat{p}_{-\Lambda} = 0.5$ and $\hat{\tau}=1$, (P2) agents with correct estimation, $\hat{p}_{-\Lambda} = 0.5$, but with precision ($\hat{\tau}$) drawn from a log-normal distribution LN(0.25, 4)[19], (P3) agents with correct precision of $\hat{\tau} = 1$ but with estimation of initial beliefs $\hat{p}_{-\Lambda}$ drawn from a uniform distribution U(0,1), and (P4) agents with estimation and precision drawn from distributions of U(0, 1) and LN(0.25, 4), respectively. The results are displayed in Figure 7.

<<INSERT FIGURE 7 HERE>>

Unsurprisingly, the population of Bayesian-rational agents (P1) exhibits the greatest net profit at all levels of $\mathbf{\Lambda}$. A population with symmetric biases in precision alone (P2) performs nearly as well as the population of Bayesian-rational agents; pre-entry learning quickly overcomes the costs of bias in this population. Relative to the population with symmetric biases only in precision (P2), the population with symmetric biases in initial estimates (P3) generates expected profits that are 50% lower for $\mathbf{\Lambda} = 0$. This deficit narrows, in percentage terms, as pre-entry learning is extended, but remains economically substantial as $\mathbf{\Lambda}$ increases. Although, as we have argued above (and Figure 5 Panel D shows), under-precision is a partial antidote to both optimism and pessimism, biases in precision and estimation (P4) are still more deleterious together than individually when evaluated at the population level. The

[19] Precision is a non-linear bias. Therefore we choose a distribution that places ½ of the agents above and ½ below the correct precision level and matches each over-precise agent with an under-precise agent with an equivalent magnitude bias (e.g., $\tau = 0.25$ matched to $\tau = 4$).

offsetting interaction between under-precision and the cost from bias in initial beliefs is more than overcome by the negative interaction between over-precision and initial beliefs in the population.

Together with prior analyses, the implications here are intriguing – biases in precision have limited negative consequences when agents have accurate initial beliefs about success prospects (i.e., when the distribution of $\hat{p}$ is tight and close to unbiased). Policy makers, educators, or investors, then, will find it more fruitful to focus on assisting agents in developing the correct initial beliefs than in remedying faulty updating processes.

4.5 The Impact of Pre-entry Learning, Entry, and Exit on Measured Bias in the Population

In this final exercise, we examine how trait-like differences between entrants and non-entrants may result in a population of nascent entrepreneurs. We assume that estimation and precision biases are unchanging traits of individuals, measurable at any point in time before or after the entry decision. We examine how selection, both into the market at entry and out of the market via exit, impacts observed precision and estimation bias (optimism or pessimism) in the population of participating firms over time. Additionally, we investigate how selection via pre-entry learning interacts with post-entry learning and exit to affect the strength of the observed relationship between profitability and these two distinct forms of confidence bias over time. In doing so, we connect our model to empirical literature that examines differences in confidence biases between populations of entrepreneurs and non-entrepreneurs (Busenitz and Barney 1997) and a similarly robust literature examining the relationship between individual-level measures of confidence bias and performance (e.g., Lowe and Ziedonis 2006, Koellinger, Minniti, and Schade 2007, Astebro, Jeffrey, and Adomza 2007).

In particular, we set k = 100 and then draw each agent's initial beliefs ($\hat{p}_{-\Lambda}$) and precision ($\hat{\tau}$) as in our examination of population P4 (in section 4.4) for pre-entry learning periods of length $\mathbf{\Lambda}$ = 0, 1, 2, and 5. We then examine the median levels of $\hat{p}_{-\Lambda}$ and $\hat{\tau}$ in the population of surviving entrepreneurs (i.e., entrants who have not yet exited) for t > 0. For surviving entrepreneurs, we also examine the correlation between contemporaneous profitability and both $\hat{p}_{-\Lambda}$ and $\hat{\tau}$, and the correlation between $\hat{p}_{-\Lambda}$ and $\hat{\tau}$. The results are displayed in Figure 8.

<<INSERT FIGURE 8 HERE>>

Exit significantly changes the distributions of bias found in the population of surviving entrepreneurs over time, as seen in Figure 8, Panels A and B. Unsurprisingly, the initial population of entrants exhibits significant over-estimation bias (optimism), which is mitigated by a longer period of pre-entry learning (see Panel A). Somewhat less obvious is that entrants initially exhibit under-precision, per the results in Panel B. The degree of under-precision exhibited by entrants in early periods is reduced by pre-entry learning. Intuitively, one may think of under-precise entrepreneurs as viewing the quality of pre-entry signals as higher than they really are. Thus, if, by chance, an agent receives a series of positive signals pre-entry, it is more inclined to enter than would a neutral-precision agent.[20]

Estimation and precision bias profiles of the population of entrants change over time, following inverse-U and U-shaped patterns, respectively. The mechanics of why this occurs are as follows. The "early exiters" may be thought of as "quitters" because they are least persistent in the industry. They exhibit greater under-estimation and under-precision (they are pessimists that respond too rapidly to new negative signals) than the representative (i.e., median) entrant. Their early exit diminishes under-precision in the surviving population of entrants, and increases the average level of optimism. In contrast, "late exiters" may be thought of as "sitters" because they are the most persistent in the industry. They exhibit greater over-estimation and over-precision than the representative entrant (they are optimists that do not respond to negative signals). Their late exit eventually diminishes over-precision optimism amongst the survivors. The net effect of these two kinds of exits, over time, is to create the curvilinear bias patterns among survivors exhibited in Figure 8, Panels A and B.

Three other aspects of survivors' patterns of bias in Panels A and B are noteworthy. First, the levels of bias in the steady state (measured at period 100, after all exit has occurred) can be either higher or lower than at entry, depending pre-entry learning duration. Second, the extent of bias fluctuation over time depends on the level of pre-entry learning. Pre- and post-entry learning are substitutes. If the

[20] Since agents are randomly endowed with estimation bias that is symmetric around zero, it might not be immediately obvious why, with no pre-entry learning, entrants are under-precise immediately post-entry (circle-marked line of panel B). The reason is as follows: an agent who is under-precise but otherwise rational will believe that new information is higher quality (less noisy) than it really is. As such, this agent will believe that the option value of entry is higher than it really is, which induces entry.

pre-entry period is short, more screening must happen post entry. Third, when it comes to precision, whether the majority of entrepreneurs in the population of firms exhibit over- or under-precision depends on when, post-entry, precision bias is measured. The implication is that cross-sectional empirical studies may systematically misestimate the amount of bias in the population of potential entrepreneurs.

In Panels C and D of Figure 8, we examine the observed correlation between profitability and individual bias traits in the surviving population (note: there is no *ex ante* correlation pre-entry). The results are straightforward and intuitive: there is an initial post-entry negative correlation between over-estimation (optimism) and profitability, similar to the relationship found in Hmieleski and Baron (2009), and likewise between over-precision (lower $\hat{\tau}$) and profitability. The magnitude of this correlation declines to zero over time post-entry as, in our model, post-entry learning effectively weeds out low-type firms. Thus, the evolution of the population over time may have important implications for interpreting existing and designing future empirical work. The strength of the correlation between bias and profitability depends critically upon when it is measured, and tests of statistical significance will fail close to steady state even if, at entry, bias had an economically significant impact.

Finally, we examine the correlation between estimation and precision bias in the population of entrants (once again, no *ex ante* correlation in the population). Despite its importance and the challenge of discriminating between these common biases, particularly given that these biases may generate somewhat similar empirical footprints (Astebro et al. 2014), no prior studies of entrepreneurship have investigated the conditions under which they are likely to co-occur or how common these conditions might be. Fortunately, our model is amenable to answering this question in depth.

In Panel E, we report the observed correlation between $\hat{p}_{-\Lambda}$ and $\hat{\tau}$ over time (note that there is no *ex ante* correlation in the population). At all levels of pre-entry learning, the selection process yields a negative correlation between estimation (initial beliefs) and precision measured across all surviving entrants. Because lower levels of $\hat{\tau}$ represent greater over-precision, this result indicates that selection into the market generates a positive correlation across the population between over-estimation (optimism) and over-precision at the individual level – this is precisely the set of agent traits that is most

counter-productive for profitability (see Figure 5, Panels C and D).

The strength of this correlation between each agent's optimism and its over-precision increases at modest levels of pre-entry learning (i.e., from $\mathbf{\Lambda} = 0$ to $\mathbf{\Lambda} = 1$) but decreases for higher levels of pre-entry learning (i.e., from $\mathbf{\Lambda} = 1$ to $\mathbf{\Lambda} = 5$). The length of the pre-entry period also shapes the dynamics of this correlation over time. For longer periods of pre-entry learning, the correlation seems to decline persistently until reaching a modest correlation in steady state. At shorter periods of pre-entry learning, the correlation first strengthens and then weakens over time, presumably as post-entry learning substitutes for the pre-entry learning that did not occur (and which would have reduced the correlation if it had).

The implications of this dual analysis of estimation and precision bias are critical for evaluating empirical studies. First, studies that attribute differences in entrepreneurial performance to a single, measured trait of estimation or precision bias will systematically over-estimate the causal relationship of the single factor, since it is likely to co-occur with the other. Second, studies that decompose the effects of each trait on performance need also consider the interaction of these traits, both because the the underlying traits are correlated in the examined population, and because the consequences of each depend critically on the presence or absence of the other.

5. DISCUSSION

By integrating pre-entry and post-entry learning in a single model, we inform prior studies that examine the relationship between pre-entry experience, ability, and performance. Elfenbein, Hamilton, and Zenger (2010), for example, interpret the performance advantage of entrants coming from small firms largely as evidence that these entrepreneurs have acquired skills enabling them to perform better in entrepreneurship. While our model does not rule this out, it suggests an alternative explanation: entrepreneurs coming from small firms may have a more accurate assessment of the quality of their opportunities and hence, their self-selection into entrepreneurship may be better. Similarly, our model suggests that observed associations between measures of general ability and performance in entrepreneurship (e.g., Hartog, Van Praag, and Van der Sluis 2010), may result from more careful

self-selection into entrepreneurship (because high-ability workers have higher opportunity costs), rather than because entrepreneurs must be jacks-of-all-trades. Finally, our model sheds light on some well-known patterns documented by scholars of industry evolution. It suggests that differences in survival rates between *de alio* vs. *de novo* entrants (e.g., Carroll et al. 1996) may also be interpreted as resulting from differences in the quality or amount of pre-entry learning about an opportunity, rather than solely from the development and transfer of capabilities (Helfat and Lieberman 2002).

In extending the model to incorporate biased agents, we move beyond providing a parsimonious explanation of broad set of empirical patterns and generate new predictions that are relevant for scholars of entrepreneurship, for policy-makers, and for prospective entrepreneurs and investors. We explore the interaction of estimation and precision biases and demonstrate that it is *precisely those entrepreneurs who perform the worst post-entry who are most likely to enter*. Furthermore, we demonstrate that positive estimation biases (optimism) and under-precision compensate for one another: agents endowed with this set of biases perform nearly as well as fully-rational agents. Moreover, these happily double-biased agents perform better than optimists who display no precision bias. The model, then, suggests that the Silicon Valley mantra, "fail fast, fail often" (Babineaux and Krumboltz 2013), may be sensible, even in a one-shot setting, i.e., one in which actors face a single opportunity. A positive initial optimism bias combined with modest over-reaction to information collected can yield near-optimal results.

Additionally, the individual-entrepreneur focus of our model enables us to examine the degree to which more (or more accurate) pre-entry learning can remedy biases either at the individual or population levels. Policy makers and educators would do well to note that, when estimation and precision biases are both present in a population, pre-entry learning overcomes bias only slowly. Our results on this convergence speed (Figure 7) suggest that remedies that improve the accuracy of agents' initial estimates of success are likely to be more cost-effective than relying purely on eventual learning and selection.

Furthermore, our analysis of how the endogenous entry and exit choices of biased agents affect

observed biases in the population of (enduring) entrants and non-entrants over time reveals the challenges inherent to empirical studies that would seek to contrast the decision-making biases of entrepreneurs and non-entrepreneurs, such as Busenitz and Barney (1997) or Forbes (2005). As Figure 8 shows, the degree of bias in a population is a function of both pre-entry learning and post-entry experience. Most significantly, the *median bias of agents in the population moves from under-precision to over-precision and back to under-precision* over time, purely as a result of exit from the market. To our knowledge, even when empirical studies of entrepreneurs' traits distinguish between different manifestations of overconfidence (which is not uniformly the case), their conclusions generally fail to recognize these important dynamics expected of all such populations. Moreover, our model predicts a correlation between estimation and precision biases among entrants; an empirically testable prediction. We are unaware of any extant models that generate similar predictions about the correlation of overconfidence-related traits or their changes over time in the population of entrepreneurs.

Our study is not, of course, without many limitations, of which we can only include a partial list here. For tractability, we abstract away from issues of effort and investment through which an entrepreneur can affect her prospects for success. Our model thus represents a process of passive, rather than active, learning (Pakes and Ericson 1998). We ignore the possibility that optimism can affect not only whether the entrepreneur exploits an opportunity, but also how (e.g., Dushnitsky 2010). Additionally, we ignore alternative mechanisms that lead to overconfidence, such as confirmatory bias, which has been shown to be empirically important in laboratory studies of exit delay (Elfenbein, Knott, and Croson 2017), or anchoring bias, which has been examined in survey-based work (Simon, Houghton, and Aquino 2000). Anchoring bias is similar to over-precision in our model, with the distinction being that a handful of early observations might be more influential than subsequent observations. Our model is amenable to examining the impact of these, and other, biases, but for simplicity we have abstracted away from them.

Furthermore, we have modeled the length of the pre-entry learning period as exogenous. Although we

believe that endogenizing the timing of entry is desirable, doing so is associated with significant complexity. Endogenizing entry timing should improve results for unbiased agents – a rational agent can do no worse when additional flexibility. Yet, it is not at all clear that the same can be said for biased agent, as the value of increased flexibility depends on the ability to exercise it optimally.; biased agents may harm themselves with additional choices. Similarly, the entrepreneurial process we model consists of a single opportunity, rather than a series of opportunities, or "pivots" (Arteaga and Hyland 2013). We leave addressing these limitations to future work.

6. CONCLUSION

Our approach offers a computational model that examines entrepreneurial decision-making as a process of learning punctuated by decisions. The model explains a number of well-documented, but heretofore independently explained, patterns of entrepreneurial behavior via a single, unified learning mechanism that begins prior to entry and, conditional on entry, continues until an exit decision is made. The model enables us to examine learning and decision-making by those who exhibit confidence biases (estimation and precision), as well as establish an explicit benchmark based on fully rational entrepreneurs, that accounts for both selection and treatment effects of the entrepreneurs' experience.

Our results make the case for caution in interpreting observed entrepreneurial behavior, such as high levels of certainty about the likelihood of success, excess entry, or delayed exit as driven primarily by behavioral bias. While a Bayesian-rational entrepreneur may act optimally conditional on her incomplete information, the decision may still appear to be mistaken or biased from the perspective of an outside observer with different (whether worse or better) information. Furthermore, when examining potentially biased samples of entrants, the co-occurrence of precision and estimation biases that the simulation model predicts suggests that studies that examine only one of these biases risk misattributing the causes of observed behavior and thus drawing incorrect implications, since these biases interact with one another and affect persistence and performance in very different ways.

7. REFERENCES

Agarwal R, Bayus BL (2002) The market evolution and sales takeoff of product innovations. *Management Science* 48(8): 1024–1041.

Agarwal R, Echambadi R, Franco AM, Sarkar MB (2004) Knowledge transfer through inheritance: Spin-out generation, development, and survival. *Academy of Management Journal*, *47*(4), 501-522.

Agarwal, R, Campbell, BA, Franco, AM, Ganco M (2016) What Do I Take With Me? The Mediating Effect of Spin-out Team Size and Tenure on the Founder–Firm Performance Relationship. *Academy of Management Journal*, 59(3), 1060-1087.

Aggarwal VA, Posen HE, Workiewicz M (2016) Adaptive capacity to technological change: A microfoundational approach. *Strategic Management Journal* 38(6): 1212–1231.

Artinger S, Powell TC (2016) Entrepreneurial failure: Statistical and psychological explanations. *Strategic Management Journal*. John Wiley & Sons, Ltd 37(6): 1047–1064.

Arteaga, R, Hyland J (2013) *Pivot: How Top Entrepreneurs Adapt and Change Course to Find Ultimate Success*. John Wiley & Sons.

Åstebro T, Herz H, Nanda R, Weber RA (2014) Seeking the roots of entrepreneurship: insights from behavioral economics. *The Journal of Economic Perspectives*, *28*(3), pp.49-69.

Åstebro T, Chen J, Thompson P. (2011) Stars and misfits: Self-employment and labor market frictions. *Management Science*, *57*(11), pp.1999-2017.

Åstebro T, Jeffrey SA, Adomdza GK (2007) Inventor perseverance after being told to quit: The role of cognitive biases. *Journal of behavioral decision making*, *20*(3), pp.253-272.

Babineaux R, Krumboltz J (2013) *Fail Fast, Fail Often: How Losing Can Help You Win*. Penguin.

Balasubramanian N (2011) New plant venture performance differences among incumbent, diversifying, and entrepreneurial firms: The impact of industry learning intensity. *Management Science* 57(3): 549–565.

Baum JR, Frese M, Baron RA, Katz JA (2007). Entrepreneurship as an area of psychology study: An introduction. *The Psychology of Entrepreneurship*, 1-18.

Benoit JP, Dubra J (2011) Apparent overconfidence. *Econometrica* 79(5): 1591–1625.

Braguinsky S, Klepper S, Ohyama A (2012) High-tech entrepreneurship. *Journal of Law and Economics* 55(4): 869–900.

Burmeister-Lamp K, Lévesque M, Schade C (2012) Are entrepreneurs influenced by risk attitude, regulatory focus or both? An experiment on entrepreneurs' time allocation. *Journal of Business Venturing*, *27*(4), pp.456-476.

Burke AE, FitzRoy FR, Nolan MA (2008) What makes a die-hard entrepreneur? Beyond the 'employee or entrepreneur' dichotomy. *Small Business Economics*, 31(2), 93-115.

Busenitz LW, Barney JB (1997) Differences between entrepreneurs and managers in large organizations. *Journal of Business Venturing*, *12*(1), pp.9-30.

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

Carroll GR, Bigelow LS, Seidel MDL, Tsai LB (1996) The fates of de novo and de alio producers in the American automobile industry 1885–1981. *Strategic Management Journal*, *17*(S1), pp.117-137.

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

Campbell JR, De Nardi M (2009) A conversation with 590 nascent entrepreneurs. *Annals of Finance*, *5*(3-4), 313-340.

Casson M (1982) *The Entrepreneur: An Economic Theory*. Barnes & Noble Books. New Jersey

Chatterji AK (2009) Spawned with a silver spoon? Entrepreneurial performance and innovation in the medical device industry. *Strategic Management Journal*, *30*(2), pp.185-206.

Chen PL, Williams C, Agarwal R (2012) Growing pains: Pre-entry experience and the challenge of transition to incumbency. *Strategic Management Journal* 33(3): 252–276.

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

Cope J (2005) Toward a Dynamic Learning Perspective of Entrepreneurship. *Entrepreneurship: Theory & Practice*, 29(4), 373-397.

Croson DC, Minniti M (2012) Slipping the surly bonds: The value of autonomy in self-employment. *Journal of Economic Psychology*. Elsevier B.V. 33(2): 355–365.

Cyert RM, DeGroot MH (1974) Rational expectations and Bayesian analysis. *Journal of Political Economy* 82(3): 521–536.

Dencker JC, Gruber M (2015) The effects of opportunities and founder experience on new firm performance. *Strategic Management Journal* 36(7): 1035–1052.

Dencker JC, Gruber M, Shah SK (2009) Pre-entry knowledge, learning, and the survival of new firms. *Organization Science* 20(3): 516–537.

DeTienne DR, Shepherd DA, De Castro JO (2008) The fallacy of "only the strong survive": The effects of extrinsic motivation on the persistence decisions for under-performing firms. *Journal of Business Venturing*, *23*(5), pp.528-546.

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

Elfenbein DW, Hamilton BH, Zenger TR (2010) The small firm effect and the entrepreneurial spawning of scientists and engineers. *Management Science*, *56*(4), pp.659-681.

Elfenbein DW, Knott AM (2015) Time to exit: Rational, behavioral, and organizational delays. *Strategic Management Journal*. John Wiley & Sons, Ltd 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 (2017): 278-299.

Eisenhardt K, Schoonhoven C (1990) Organizational growth - linking founding team, strategy, environment, and growth among United-States semiconductor ventures, 1978-1988. *Administrative Science Quarterly* 35(3): 504–529.

Evans DS, Leighton LS (1989) Some empirical aspects of entrepreneurship. *The American Economic Review*, 519-535.

Folta TB, Delmar F, Wennberg K, (2010) Hybrid entrepreneurship. *Management Science*, 56(2), 253-269.

Forbes DP (2005). Are some entrepreneurs more overconfident than others?. *Journal of Business Venturing*, *20*(5), pp.623-640.

Frank MZ (1988) An intertemporal model of industrial exit. *The Quarterly Journal of Economics* 103(2): 333–344.

Ganco M, Agarwal R (2009) Performance differentials between diversifying entrants and entrepreneurial start-ups: A complexity approach. *The Academy of Management Review* 34(2): 228–252.

Garland, H (1990) Throwing good money after bad: The effect of sunk costs on the decision to escalate commitment to an ongoing project. *Journal of Applied Psychology* 75(6) : 728.

Gimeno J, Folta TB, Cooper AC, Woo CY (1997). Survival of the fittest? Entrepreneurial human capital and the persistence of underperforming firms. *Administrative Science Quarterly* 42(4):750-783.

Gittins J (1989) *Multi-armed bandit allocation indices*. New York: John Wiley and Sons.

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

Hartog J, Van Praag M, Van Der Sluis J (2010) If you are so smart, why aren't you an entrepreneur? Returns to cognitive and social ability: Entrepreneurs versus employees. *Journal of Economics & Management Strategy* 19(4): 947–989.

Hayward, ML, Shepherd DA, Griffin D (2006). A hubris theory of entrepreneurship. *Management*

Science, *52*(2): 160-172.
Headd B, Nucci A, Boden R (2010) What matters more: Business exit rates or business survival rates? *Washington, DC: United States Census Bureau's Business Dynamics Statistics.*
Helfat CE, Lieberman MB (2002) The birth of capabilities: market entry and the importance of pre-history. *Industrial and Corporate Change*, *11*(4), pp.725-760.
Hmieleski KM, Baron RA (2009) Entrepreneurs' optimism and new venture performance: A social cognitive perspective. *Academy Of Management Journal* 52(3): 473–488.
Hogarth RM, Karelaia N (2012) Entrepreneurial success and failure: Confidence and fallible judgment. *Organization Science* 23(6): 1733–1747.
Johnson MD, Anderson EW, Fornell C (1995) Rational and adaptive performance expectations in a customer satisfaction framework. *Journal of Consumer Research* 21(4): 695–707.
Jovanovic B (1982) Selection and the Evolution of Industry. *Econometrica*, *50*(3), pp.649-670.
Klepper S (2002) The capabilities of new firms and the evolution of the US automobile industry. *Industrial and Corporate Change* 11(4): 645–666.
Klepper S, Sleeper S (2005) Entry by spinoffs. *Management Science*, *51*(8), pp.1291-1306.
Klepper S, Thompson P (2010) Disagreements and intra-industry spinoffs. *International Journal of Industrial Organization*, *28*(5), pp.526-538.
Knight FH (1921) *Risk, Uncertainty and Profit.* Hart, Schaffner and Marx. New York
Koellinger P, Minniti M, Schade C (2007) "I think I can, I think I can": Overconfidence and entrepreneurial behavior. *Journal of Economic Psychology*, *28*(4): 502-527.
Lowe RA, Ziedonis AA (2006). Overoptimism and the performance of entrepreneurial firms. *Management Science*, *52*(2):.173-186.
Mankiw NG, Whinston, MD (1986) Free entry and social inefficiency. *RAND Journal of Economics* 17(1), pp. 48-58.
March JG, Olsen JP (1975) The uncertainty of the past: organizational learning under ambiguity*. *European Journal of Political Research*, *3*(2), pp.147-171.
March JG, Sproull LS, Tamuz M (1991). Learning from samples of one or fewer. *Organization Science*, *2*(1):1-13.
McMullen JS, Shepherd DA (2006) Entrepreneurial action and the role of uncertainty in the theory of the entrepreneur. *Academy of Management Review* 31(1): 132–152.
Minniti M, Bygrave W (2001) A dynamic model of entrepreneurial learning. *Entrepreneurship: Theory and Practice*, 25(3), 5-17.
Moeen M, Agarwal R (2017) Incubation of an industry: heterogeneous knowledge bases and modes of value capture. *Strategic Management Journal*, *38*(3), pp.566-587.
Moore DA, Healy PJ (2008) The trouble with overconfidence. *Psychological Review*, *115*(2), p.502.
Moskowitz TJ, Vissing-Jorgensen A (2002) The returns to entrepreneurial investment: a private equity premium puzzle?. *American Economic Review*, *92*(4), pp.745-778.
Navis C, Ozbek OV (2015) The right people in the wrong places: The paradox of entrepreneurial entry and successful opportunity realization. *The Academy of Management Review* 41(1): 109–129.
O'Brien J, Folta T (2009) Sunk costs, uncertainty and market exit: A real options perspective. *Industrial and Corporate Change* 18(5): 807–833.
Oaksford M, Chater N (2009) Precis of Bayesian rationality: The probabilistic approach to human reasoning. *Behavioral and Brain Sciences*, *32*(1):.69-84.
Pakes A, Ericson R. (1998). Empirical implications of alternative models of firm dynamics. *Journal of Economic Theory*, 79(1), pp.1-45.
Parker SC (2006). Learning about the unknown: How fast do entrepreneurs adjust their beliefs. *Journal of Business Venturing*, 21(1), 1-26.
Parker SC, Belghitar Y (2006) What happens to nascent entrepreneurs? An econometric analysis of the

PSED. *Small Business Economics*, 27(1), 81-101.
Petrova K (2012) Part-time entrepreneurship and financial constraints: evidence from the Panel Study of Entrepreneurial Dynamics. *Small Business Economics*, 39(2), 473-493.
Politis D (2005) The process of entrepreneurial learning: A conceptual framework. *Entrepreneurship Theory and Practice*. Blackwell Publishing Ltd. 29(4): 399–424.
Posen HE, Chen JS (2013) An advantage of newness: Vicarious learning despite limited absorptive capacity. *Organization Science*, *24*(6), 1701-1716.
Posen HE, Levinthal DA (2012). Chasing a moving target: Exploitation and exploration in dynamic environments. *Management Science*, *58*(3), 587-601.
Qian L, Agarwal R, Hoetker G (2012) Configuration of value chain activities: The effect of pre-entry capabilities, transaction hazards, and industry evolution on decisions to internalize. *Organization Science* 23(5): 1330–1349.
Raffiee J, Feng J (2014). Should I quit my day job?: A hybrid path to entrepreneurship. *Academy of Management Journal* 57(4): 936-963.
Ravasi D, Turati C (2005) Exploring entrepreneurial learning: A comparative study of technology development projects. *Journal of Business Venturing* 20(1): 137–164.
Reynolds PD, Carter NM, Gartner WB, Greene PG (2004) The prevalence of nascent entrepreneurs in the United States: Evidence from the panel study of entrepreneurial dynamics. *Small business economics*, 23(4), 263-284.
Roach M, Sauermann H (2015) Founder or joiner? The role of preferences and context in shaping different entrepreneurial interests. *Management Science*, *61*(9), 2160-2184.
Ryan R, Lippman SA (2003) Optimal exit from a project with noisy returns. *Probability in the Engineering and Informational Sciences*, 17(4), pp.435-458.
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), pp. 113-134.
Shane SA (2008) *The Illusions of Entrepreneurship.* Yale University Press.
Sørensen JB (2007) Bureaucracy and entrepreneurship: Workplace effects on entrepreneurial entry. *Administrative Science Quarterly*, *52*(3), pp.387-412.
Sørensen JB, Phillips DJ (2011) Competence and commitment: employer size and entrepreneurial endurance. *Industrial & Corporate Change*, *20*(5), 1277-1304.
Staw BM (1981) The escalation of commitment to a course of action. *Academy of management Review*, *6*(4), pp.577-587.
Van den Steen E (2011) Overconfidence by Bayesian-rational agents. *Management Science* 57(5): 884–896.
Van Praag CM, Cramer JS (2001) The roots of entrepreneurship and labour demand: Individual ability and low risk aversion. *Economica*, 68(269), 45-62
von Mises L (1949). *Human Action: A Treatise on Economics*. Yale University Press. New Haven, CT
von Weizsacker CC (1980) A welfare analysis of barriers to entry. *Bell Journal of Economics* 11(2), 399-420.
Weinhardt JM, Petricevic O, Davis, J (2015) The role of confidence in the new venturing process. Working Paper, University of Alberta.
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.
Wu B, Knott AM (2006) Entrepreneurial risk and market entry. *Management Science*, *52*(9): 1315-1330.

8. FIGURES

Figure 1. Verbal description of model assumptions, mechanisms, and results

Assumptions

Agents

- Each agent has an opportunity that is either Type H (profitable) or Type L (unprofitable)
- Agents don't know their opportunity type, but begin with initial beliefs about likelihood their opportunity is Type H, Pr(Type = H)
- Maximize profits conditional on beliefs
- Incorporate value of abandonment option in entry decision, and value of learning in decision to continue or exit

Unbiased Agents

- Initial beliefs about likelihood of success and noisiness of profit signals are correct

Biased Agents

- Initial beliefs about Pr(Type = H) may be too high (*initial optimism*) or too low (*initial pessimism*)
- Beliefs about profit signal noise may be too high (*over-precision*) or too low (*under-precision*)

Learning

- Learning starts before entry and continues until the time of the exit decision
- Agents know that profit signals, pre- and post-entry come from normal distributions with means (μ_H) and (μ_L), for Type-H and Type-L opportunities, respectively
- Agents update beliefs about the probability they are Type H based on profit signals pre- and post-entry consistent with Bayes Rule and their beliefs about the noisiness of the profit signals

Mechanisms

- **Pre-entry learning** shapes distribution of agents' beliefs at the moment prior to entry about Pr(Type = H)
  - beliefs at moment of entry correspond to an expected value, conditional on optimally exercising option to abandon
- Agents **enter only if beliefs correspond to an expected value that exceeds entry cost**
  - beliefs must be 'high enough' to exceed an entry threshold
- Entrants **continue to update beliefs after entry**
  - exit if post-entry beliefs about fall below an exit threshold, which balances the cost of continuation with the value of learning and reducing the likelihood of an exit mistake

- **Mistaken entry of Type L agents.** Some Type-L agents do not receive negative-enough signals in the pre-entry learning period and enter the market
- **Exit Delay by Type L entrants.** Only Type-L entrants with sufficiently high belief enter the market. The higher their initial beliefs, the longer it takes them to become sufficiently pessimistic about prospects to exit
- **Mistaken non-entry of Type H agents.** When the pre-entry period is limited, some Type-H agents receive 'misleading' signals and do not enter
- **Mistaken exit by Type H entrants.** Type-H entrants may receive negative signals post-entry and decide to exit

Results

Rational Agents

- With pre-entry learning, entrants average beliefs' exceed *ex ante* likelihood of success
- Higher entry cost → lower overall entry and a higher proportion of Type-H entry
- Longer pre-entry learning → higher proportion of Type-H entry. Overall impact of learning depends on entry cost
- Higher entry cost → later exit by Type-L entrants
- Relationship pre-entry learning duration and exit delay by Type-L depends on entry cost
  - at low entry cost, exit delay by type-L falls
  - at higher entry cost exit delay by type-L rises with pre-entry learning

Biased Agents

- Entrants with *initial optimism* and *over-precision* biases enter disproportionately
- Entrants with *initial optimism* and *over-precision* biases generate the lowest post-entry profits
- Agents with modest *initial optimism* and modest *under-precision* perform nearly optimally
- *Over-precision* exacerbates the cost of *initial optimism* and *initial pessimism*
- *Precision* biases alone have little impact on expected net profits
- Longer pre-entry learning corrects bias
  - speed of correction depends on the combination of biases held by the agent
- Entry and exit change the levels of *initial estimation bias* and *precision bias* in the population over time

Figure 2. Timing of computational model and evolution of agent populations

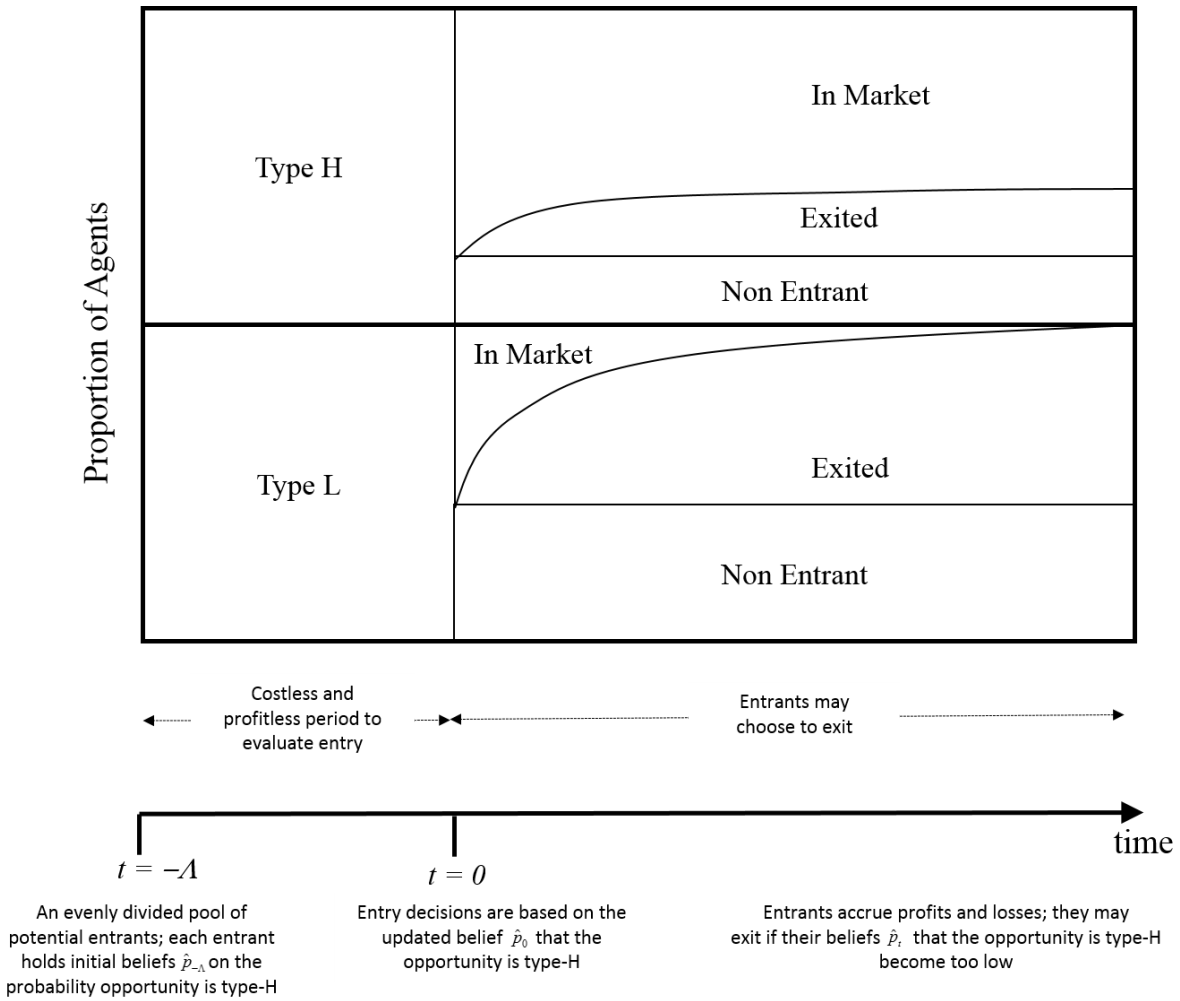
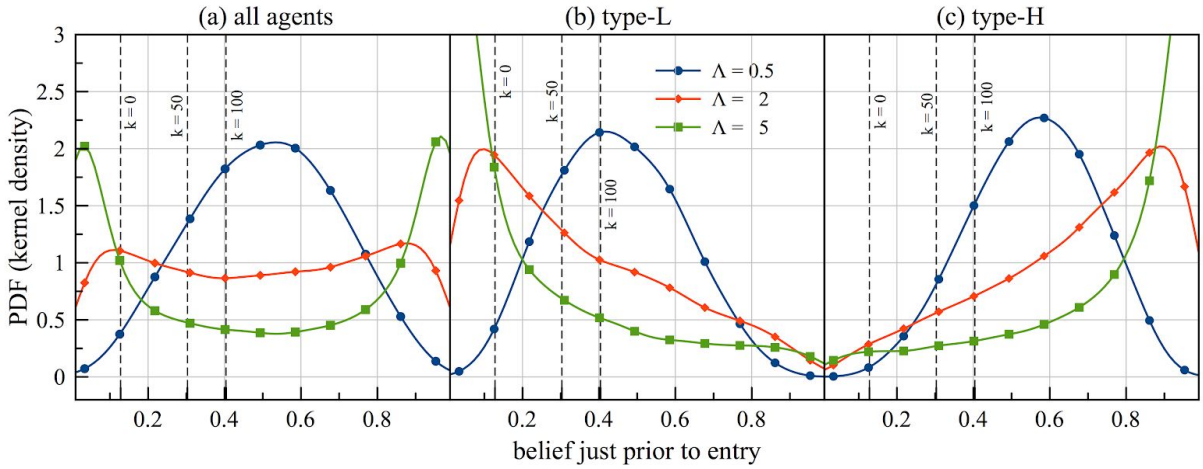
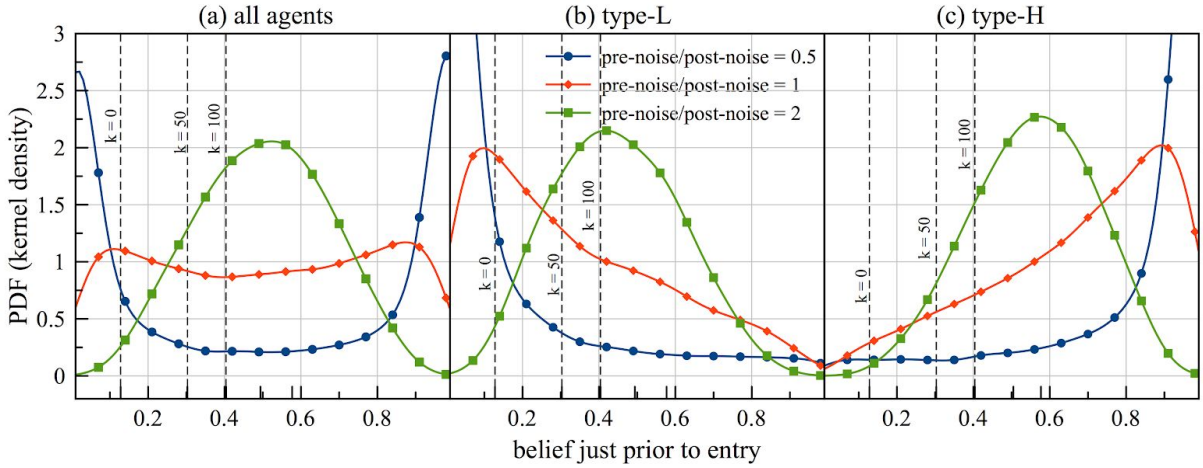


Figure 3: Distribution of agents' beliefs immediately prior to the entry decision

Panel A: Beliefs as a function of pre-entry learning duration

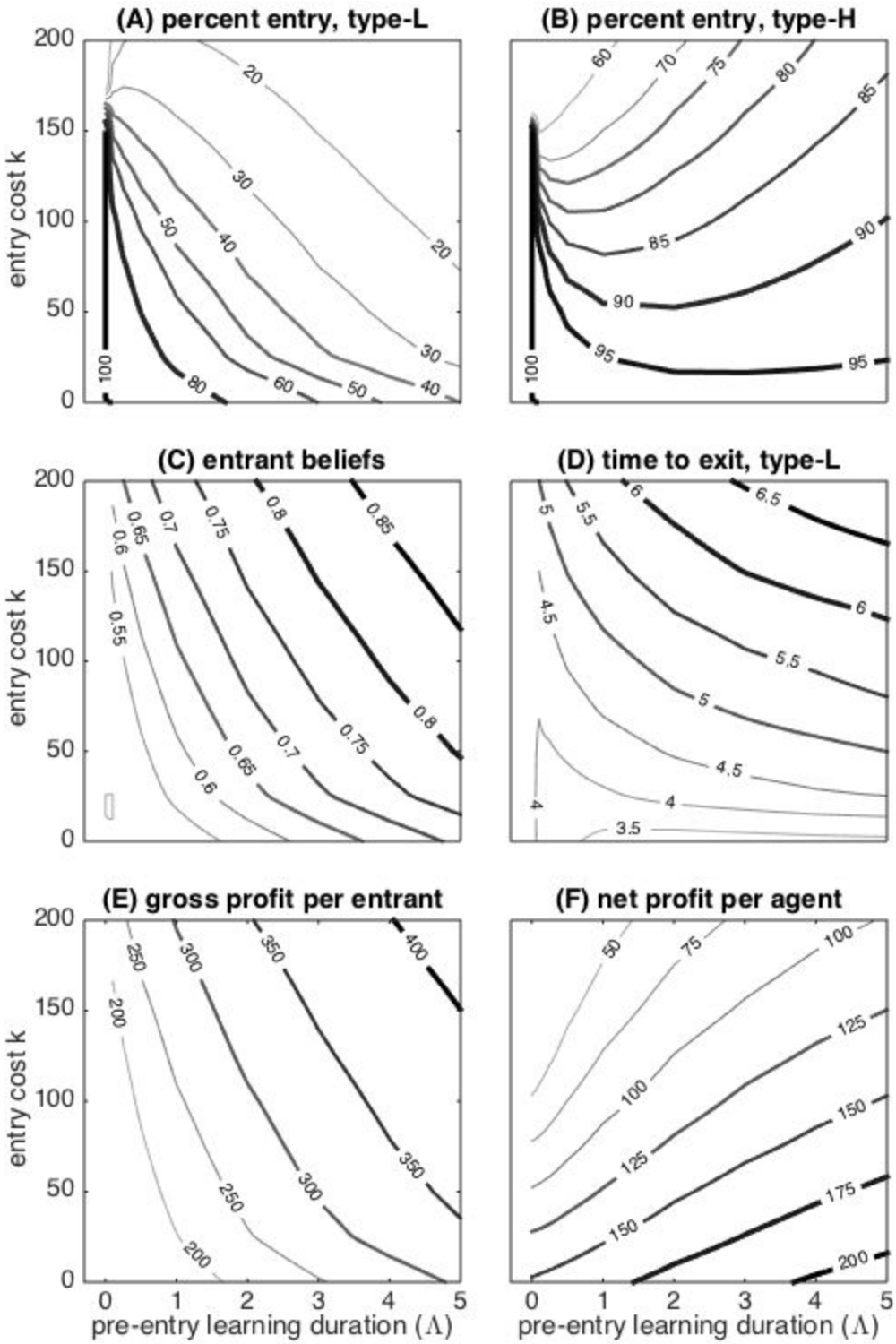


Panel B: Beliefs as a function of pre-entry learning noise



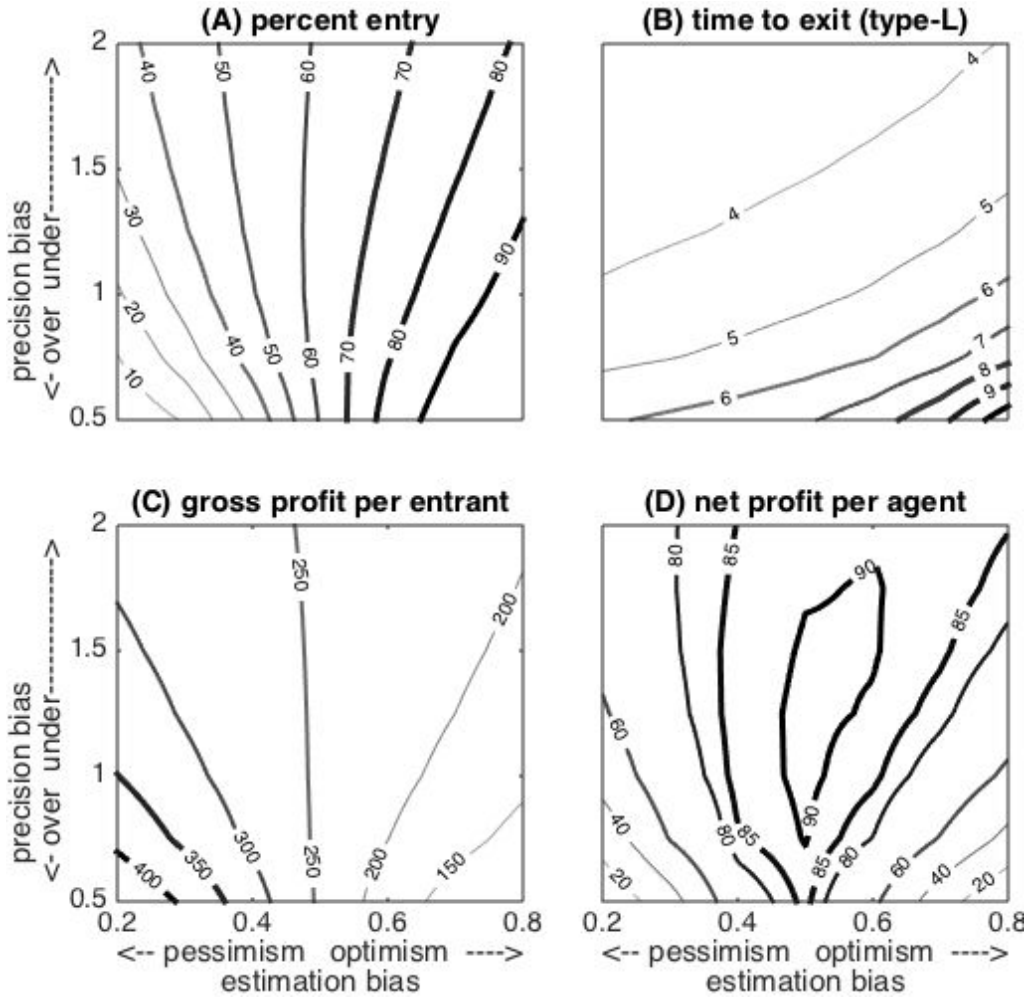
Note: In Panel A, we hold pre-and post-entry values of $\boldsymbol{\sigma}$ constant 100 and vary the length of the pre-entry learning period, $\boldsymbol{\Lambda}$, across the lines. In Panel B, we hold the length of the pre-entry learning period $\boldsymbol{\Lambda} = 2$ constant and vary the level of noise, $\boldsymbol{\sigma}$, in the pre-entry period across the lines; the agent's entry decision is based on a constant expected level of noise in the post-entry period of $\boldsymbol{\sigma} = 100$. For each value of $\boldsymbol{\Lambda}$ or noise level, we simulate 10,000 agents. Vertical dashed lines are, for the indicated entry cost, the lowest belief for which an agent will choose to enter.

Figure 4. Entry, exit, and performance for unbiased agents, as a function of k and Λ



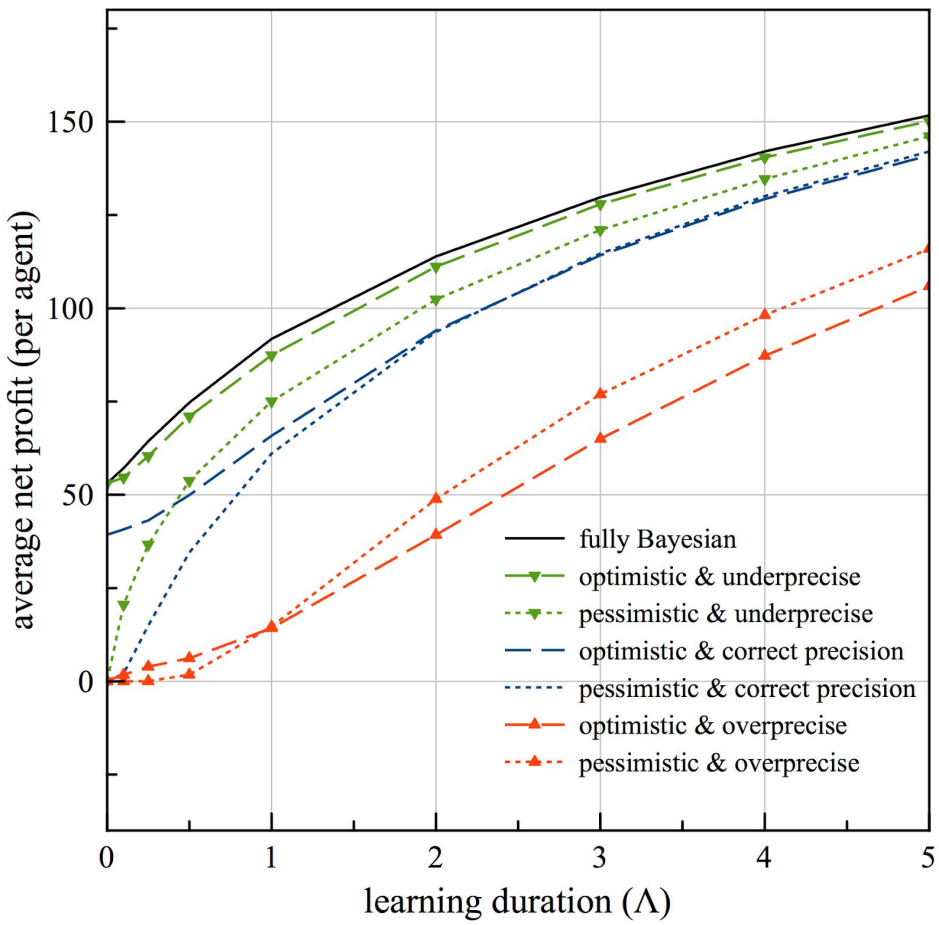
Note: All panels in the figure are based off of grid points generated as follows: for each grid point (**Λ**, k), we simulate 1,000,000 agents in our learning model with the default parameters and unbiased (Bayesian) values for $\hat{p}_{-\Lambda}$ and $\hat{\tau}$ (0.5 and 1, respectively).

Figure 5. Impact of bias on entry, exit and performance



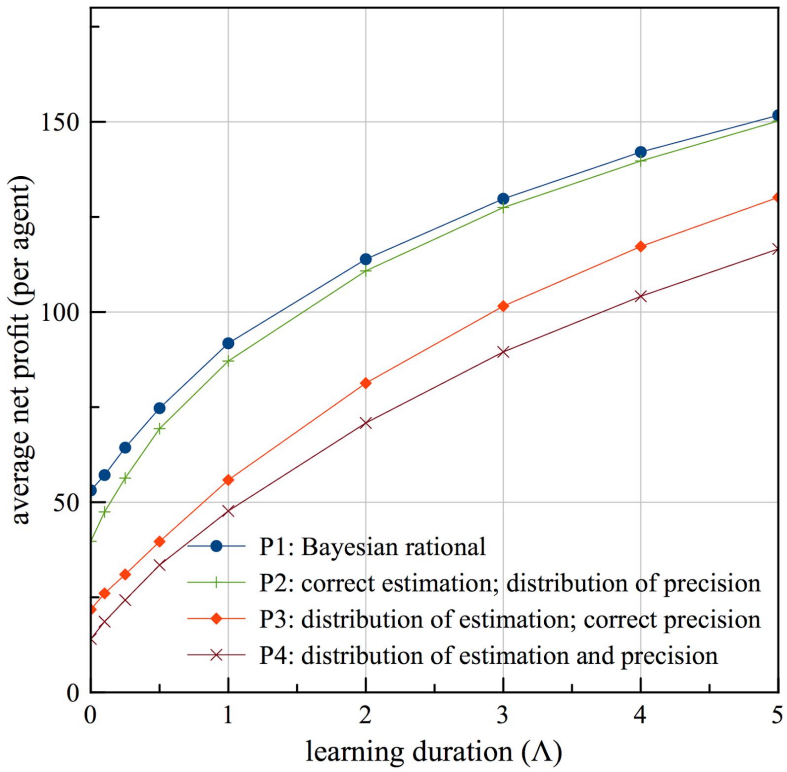
Note: All panels in the figure are based off of grid points generated as follows: for each grid point ($\hat{p}_{-\Lambda}$, $\hat{\tau}$), we simulate 10,000,000 agents in our learning model with the default parameters and (**Λ**, k) = (1, 100). Panels show percent entry, time to exit, entrant profit, net present value for agents as a function of precision and optimism bias. In Panel D, the maximum is 91.3.

Figure 6. Comparison of net profit per agent as a function of pre-entry learning for biased and unbiased agents



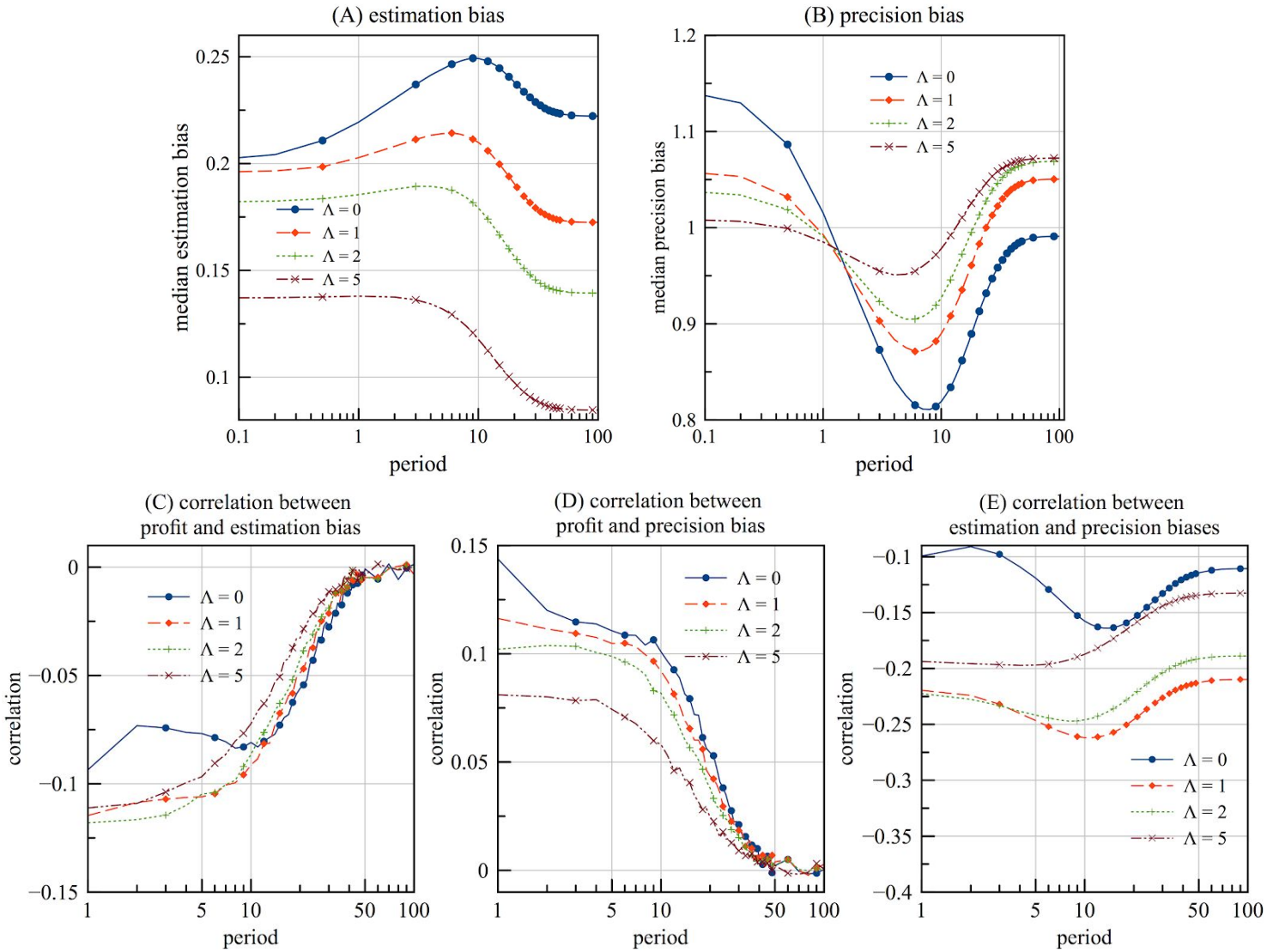
Note: For each bias profile, we simulate 1,000,000 agents at various values of **Λ** to trace out a curve. The solid black line ("fully Bayesian") represents agents who begin represents $\hat{p}_{-\Lambda} = 0.5$ and $\hat{\tau} = 1$. Pessimistic refers to agents who begin with $\hat{p}_{-\Lambda} = 0.25$; optimistic agents begin with $\hat{p}_{-\Lambda} = 0.75$. Bayesian updater refers to agents with $\hat{\tau} = 1$; over-precise agents have $\hat{\tau} = 0.5$ and under-precise agents have $\hat{\tau} = 2$. k = 100 for all cases.

Figure 7. Net profit as a function of pre-entry learning in populations of agents characterized by distributions of biases



Note: For each distributional profile, we simulate 1,000,000 agents at various values of **Λ** to trace out a curve. Distribution of estimation bias is drawn from a uniform $U(0,1)$ distribution. Since precision is a non-linear bias, the distribution of precision bias is drawn from a log uniform logU(0.25, 4) distribution. That is, we take precision to be $\hat{\tau} = 2^X$, where $X \sim U[log_2(0.25),\ log_2(4)]$. k = 100 across all cases.

Figure 8. Evolution of population-level bias 'traits' of survivors post-entry



Note: We simulate 1,000,000 agents at various values of **Λ** to trace out a curve. Random initial beliefs are drawn from a uniform $U(0,1)$ distribution. Since precision is a non-linear bias, random precision is drawn from a log uniform logU(0.25, 4) distribution. That is, we take precision to be $\hat{\tau} = 2^X$, where $X \sim U[log_2(0.25),\ log_2(4)]$. k = 100 across all cases. In panel A, values above 1.0 represent under-precision and values below 1.0 represent over-precision. In panel B, values above 0 represent optimistic initial beliefs, and values below 0 represent pessimistic initial beliefs. Panels C (and D) examine the correlation between contemporaneous profitability – that is, the incremental profit between period *t* and *t-1* – and optimism (and precision).