Equity Stakes and Exit: An Experimental Approach to Decomposing Exit Delay

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Abstract

Despite evidence that delayed exit is a pervasive and consequential problem, relatively little is known about its causes. Moreover, the study of exit delay is confounded by the fact that behavioral theories arising in the literature on escalation of commitment and economic theories that incorporate option value both yield predictions that delay increases in sunk costs and uncertainty. We construct a laboratory experiment that enables us to compare the timing of participants' exit decisions with optimal choices that incorporate option value in the absence of sunk costs. We show that receiving equity stakes – the actual cash flows of the enterprise and control rights over continuation – generates delay beyond the optimal exit point for participants allocated to unprofitable firms. While participants with equity stakes make decisions that are nearly optimal given their beliefs, their beliefs are significantly distorted relative to a control group that does not receive equity stakes. The pattern of distortion is consistent with confirmatory bias and motivated reasoning. More generally, we show that incentives affect decision making not only by affecting the payoffs of different outcomes but also by distorting information processing, which in turn affects how decision-makers sees the relative likelihood of different outcomes. This suggests that existing principal-agent models may be incomplete.

Keywords: behavioral strategy, escalation of commitment, behavioral bias, real options, exit

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1. Introduction

"Man prefers to believe what he prefers to be true."

– Sir Francis Bacon

Exit delay—persisting in a venture when evidence indicates it will be unprofitable—is a substantial economic problem for entrepreneurs and managers alike (Porter 1976, Dranikoff, Koller and Schneider 2002, Horn, Lovallo, and Viguere 2006, Guler 2007, Astebro, Jeffrey and Adomza 2007, DeTienne, Shepard and Castro 2008, Wennberg et al. 2010). Prior work has examined exit delay, or failure to exit entirely, as a function of non-pecuniary motives (Gimeno et al. 1997, Meyer and Zucker 1989), agency problems (e.g., Jensen 1993), and individual and organizational decision-making biases, frequently labeled escalation of commitment (Staw 1976, 1981, Staw and Ross 1978, Camerer and Lovallo 1999, Lowe and Ziedonis 2006). The study of exit delay is complicated by the fact that, against the backdrop of uncertainty, waiting may have option value (Dixit 1989, Ryan and Lippman 2003, Sandri et al 2010, Elfenbein and Knott 2013). Efforts to take this rational delay into account have been hampered by an inability to precisely identify an optimal exit point arising from the option value. Similarly, efforts to quantify the extent of behavioral delay have been complicated by an inability to pinpoint the specific mechanisms driving delay.

We address these deficiencies by constructing a laboratory experiment in which participants are randomly allocated to firms of unknown quality (*ex ante* half are profitable) and must make inferences about the firm's type and exit decisions based upon noisy signals of performance. We compare the inferences and exit behavior of a treatment group (*entrepreneurs*) and a control group (*advisors*). Participants in both groups receive identical information about the performance of their ventures and are provided equivalent incentives to estimate the likelihood of being allocated to a profitable firm. In addition to the compensation for providing accurate beliefs, entrepreneurs also have "equity stakes" – they receive the profits (or losses) of the firm to which they are allocated and given control rights allowing them to shut down their firm.[1] The experiment employs the structure of information and payoffs in the Ryan and

[1] What distinguishes equity stakes here versus the real world is that they are not transferable (although in the case of failure, this point is moot). We use the term equity stakes rather than equity incentives (e.g., Armstrong, Larcker,

Lippman (2003) model of optimal exit from a project with noisy returns. This allows us to characterize the optimal exit point, and compare the behavior of both groups to that baseline. We can, therefore, examine whether exit beyond the optimum occurs in the absence of sunk costs, agency problems, or other organizational phenomena, and the degree to which exit delays may be driven by equity-like compensation.

Optimal exit in the Ryan and Lippman model is defined by two parameters: current period beliefs regarding the probability of being a profitable firm, and a belief threshold for exit. The experimental setting allows us to observe the evolution of participants' beliefs about their likelihood of being a profitable firm and also allows us to characterize those beliefs at exit. By asking participants to estimate the likelihood they are profitable each period, and incentivizing them to provide accurate beliefs via a proper scoring mechanism (Holt 2007: 384-385), we can determine the extent to which exit behavior is driven by thresholds and/or beliefs. Moreover, we are able to determine the extent to which deviations from optimal exit decision-making, as defined by Ryan and Lippman, are driven by differences in exit thresholds or differences in beliefs. If there is behavioral delay (defined as exit beyond the RL optimum), the experiment further enables us to distinguish between mechanisms that affect a participants' priors (such as anchoring and status quo bias) from those affecting updates (such as confirmatory bias and motivated reasoning).

While the experiment corroborates some prior results regarding the existence of entrepreneurial exit delay (e.g., Astebro et al. 2007, Sandri et al. 2010), we obtain intriguing new results. First, we show that equity stakes can be a sufficient condition for exit delay under uncertainty. More than 70 percent of entrepreneurs allocated to unprofitable firms exit two or more periods beyond the optimum, and nearly 29 percent fail to exit altogether. By contrast, the advisor control group, whose only difference from the entrepreneur group is lack of equity stakes, tends to exit near the RL optimum – 43 percent of advisors recommend exit within one period (plus or minus) of the optimal exit period, and only 7 percent of advisors fail to recommend exit altogether.[2] In showing that equity stakes can be sufficient to generate exit, we demonstrate implicitly that sunk costs are *not* a necessary conditions for delayed exit. This is

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Ormazabel, and Taylor 2013), because equity incentives include options, which can be distortionary in that there is limited downside risk. Here entrepreneurs incur losses if they fail to exit.

[2] The experiment involves two simulations of 11 and 8 periods, respectively. In both simulations, the optimal exit period is period 4.

important in that both economic theories (Dixit 1989, Krugman 1989) and behavioral theories (Staw 1976, Staw and Ross 1978) of exit both relay on sunk cost assumptions.

Second, we show that equity stakes both help and hinder exit decision-making. In particular, the exit thresholds of entrepreneurs are significantly lower and are *closer to the rational benchmark level* defined by the RL model than the exit thresholds of advisors. We interpret this as indicating that equity stakes induce some rational delay. At the same time, participants in the entrepreneur treatment allocated to unprofitable firms form beliefs that are significantly rosier (more than 10 percentage points higher) than the beliefs held by advisors allocated to unprofitable firms, despite having initial beliefs that are statistically indistinguishable and despite receiving identical performance information. This provides evidence of behavioral delay, and shows that equity stakes induce behavioral delay by affecting beliefs.

Third, we shed some light on the mechanisms that underpin behavioral delay and the divergence of beliefs between entrepreneurs and advisors. We estimate a model of belief updating and show that while entrepreneurs and advisors' beliefs respond, on average, nearly identically to better-than-expected information, entrepreneurs responses to worse-than-expected information are significantly muted relative to advisors' responses.[3] The parameters values we estimate are consistent with confirmatory bias and motivated reasoning, but are not consistent with anchoring or status quo bias.

Finally, because we cannot observe the true exit thresholds of participants who fail to exit when allocated to unprofitable firms, we perform additional analysis on the relationship between individual characteristics and failure to exit entirely. While we find no evidence that failure to exit is associated with risk tolerance or ability in mathematics and statistics, we do find that greater internal locus of control is associated with a lower likelihood of failing to exit, and that knowledge overconfidence is associated with a greater likelihood of doing so.

Together, these findings begin to open the black box of exit delay. Our finding that equity stakes may, in-and-of themselves, induce exit delay are in contrast to prior work that attributes escalation of commitment to sunk cost fallacy, self-serving attribution bias, and associated organizational decision-making phenomena. Moreover, we suspect that the finding that equity

[3] Both groups display an asymmetry in response to "good news" vs. "bad news" but the asymmetry in response among entrepreneurs is nearly twice as large as that of advisors.

stakes affect the evolution of beliefs may come as a surprise to organizational economists. Typical models in organizational economics assume that incentives shape behavior conditional on beliefs. This experiment suggests that incentives play a significant role in shaping beliefs as well. Finally, our results highlight some reasonable approaches to reducing behavioral delay including, giving decision rights to parties without equity stakes, providing guidance from advisors without equity stakes, and using personality tests to identify entrepreneurs who *ex ante* are more likely to fail to exit in the face of (overwhelmingly) poor performance.

We contribute to a small prior literature using experiments to examine exit behavior. Ansic and Pugh (1999) examine entry and exit decisions in the face of exchange rate uncertainty. They test Krugman's (1989) model of trade hysteresis, by characterizing the entry and exit thresholds in the presence of sunk entry costs. They show that exit delay (hysteresis) increases with the entry cost and exchange rate volatility and implicitly interpret all delay as rational. In the management literature, Khavul et al (2009) conduct a psychology experiment on exit in which participants reported the likelihood (0 to 100) they would authorize funds to complete a venture capital project in the face of a negative signal (not authorizing funds is equivalent to exit). What varied across participants was the level of prior investment and percent of project remaining. They find that likelihood of exit decreases in sunk cost, and implicitly interpret all delay as behavioral (escalation of commitment). Because we recognize and attempt to decompose delay into rational and behavioral components, our work is most closely related to Sandri et al. (2010). They examine whether participants with equity-based compensation exit according to classical investment theory (when the net present value of profits is negative) or whether they take into account the option value of additional information. They find first that exit is consistent with option value (as do we). They also find that the extent of delay increases with uncertainty, and attribute this increase to behavioral delay. While there conclusion regarding behavioral delay is inferential, we investigate the sources of this behavioral delay directly. Further, to our knowledge ours is the first exit experiment to include a control group—this feature is what allows us to isolate the mechanisms driving behavioral delay. More broadly, we contribute to the literature that seeks to understand the psychological underpinnings of management behavior (Powell Lovallo and Fox 2011, Levinthal 2011) and to experimental investigations of the impact of incentives on strategic decision-making (e.g., Agarwal, Croson and Mahoney 2010, Croson, Anand and Agarwal 2007).

The remainder of this paper is organized as follows. Section 2 reviews the prior theoretical literature on exit delay and entrepreneurial exit. Section 3 describes the experimental design and data collection. Section 4 presents the results of the experiment. We analyze in turn entrepreneurs' exit decisions relative to the optimum and relative to advisors, differences in the evolution of beliefs between entrepreneurs and advisors, and links between personality characteristics and exit behavior. Section 5 concludes.

2. Theory

2.1 Optimal Exit under Uncertainty

The goal of the study is to characterize the extent and form of behavioral biases in making exit decisions. This requires that we define delay relative to a rational benchmark. The classical benchmark is exiting markets when the expected net present value (NPV) of profits becomes negative. This so-called Marshallian exit condition (Marshall 1920) obligates firms to shut down if anticipated future revenues are less than the sum of operating costs plus exit cost. This simple view, however, abstracts away from a number of important real-world features of economic decision-making. It is now well known that under conditions of uncertainty—either about the future evolution of demand (combined with sunk costs of re-entry a la Dixit 1989) or about the firm's own cost structure (Jovanovic 1982)—there is option value associated with continuing operations. Thus, managers may rationally choose to persist in business when their information set indicates that the net present value of expected profits (from continuing the business in perpetuity) is negative.

In defining optimal exit, we focus on a setting patterned after Jovanovic's (1982) theory of industry evolution via noisy selection. In Jovanovic's model, firms and potential entrants know the entire equilibrium price sequence and the distribution of firm costs, but potential entrants face *ex ante* uncertainty regarding their own cost (ability uncertainty). Firms pay a sunk cost to enter the market, then begin receiving noisy signals about their ability through participation in the marketplace. The focal firm maximizes the expected value of profits in each period by choice of output, given its knowledge about the market cost distribution, priors about its own cost, and updates associated with the stream of profit signals. Inefficient firms optimally exit the industry when the option value of waiting for additional signals is negative.

Ryan and Lippman (2003) examine a closely related problem—a manager must make a decision to continue or shut down a project of unknown quality based on noisy performance information—and must make several simplifying assumptions that enable the option value of waiting for new information and the optimal exit time to be defined precisely.. To connect with our setting, we refer to the RL manager an "entrepreneur" and the project as a "firm" in the characterization that follows.

The RL model assumes firms are of two types: with probability P_0, the firm is profitable, and has an underlying profit rate, $\mu_H > 0$. With probability 1- P_0 the firm is unprofitable, with an underlying profit rate, $\mu_L < 0$. Entry is profitable in expectation, with $P_0\, \mu_H + (1- P_0)\, \mu_L > 0$, and future profit streams are discounted at rate δ. Although entrepreneurs don't know their firm's type, it gradually becomes revealed over time through the observed stream profits. The stream of profits serves as a set of signals regarding true profitability. Each signal comprises the underlying rate, μ_H, plus a noise component with variance σ^2. Cumulative profits, X_t, thus, exhibit Brownian motion with drift μ and variance σ^2.

Although the entrepreneur does not know the firm's type, he knows the values of μ_H and μ_L, the *ex ante* probability of being a high type, P_0, and the noise, σ^2, associated with the profit signal. Bayes Rule, then, can be used to infer at any point in time, t, the posterior probability, P_t, that the firm is high-profit. Ryan and Lippman show that P_t is a function of cumulative profits, X_t, signal volatility, σ^2, the profit rates in each state, μ, and a discount rate, δ, but is independent of the pattern of profits:

$$P_t = \left[1 + \frac{1-p_0}{p_0} exp\left\{-\frac{\mu_H-\mu_L}{\sigma^2}\left(X_t - \frac{\mu_H+\mu_L}{2}t\right)\right\}\right]^{-1} \quad (1)$$

In addition to deriving the functional form for evolving beliefs, P_t, Ryan and Lippman derive a closed form solution for the optimal stopping rule. According to this rule, the optimal exit time is the first instance (i.e., the smallest value of t) at which the probability of being high type, P_t, falls below p^*:

$$p^* = \frac{(-\mu_L)(\gamma-1)}{\mu_H(\gamma+1)+(-\mu_L)(\gamma-1)} \qquad \text{with } \gamma = \sqrt{1 + \frac{8\delta\sigma^2}{(\mu_H-\mu_L)^2}} \quad (2)$$

Conforming to the optimal stopping rule maximizes expected net present value.[4] Not surprisingly, $p*$ is less than $\bar{p} = \frac{-\mu_L}{\mu_H - \mu_L}$, which defines the zero expected profit condition (Marshallian exit) in this setting. Ryan and Lippman (2003) show that the posterior probability below which exit is optimal, $p*$, is less than $\bar{p}$, for all parameter values. Thus, decision-makers who rationally incorporate the value of learning created by the real option to shut down will exit later than those who do not.

We define *delay* as exit after—or, alternatively, continuation beyond—the economically optimal exit point for unprofitable firms.[5] In our experimental context this is the earliest point at which the true posterior probability of being a high profit firm, i.e., P_t defined by equation (1) above, falls below the exit threshold, $p*$, defined by equation (2).[6]

2.2. Behavioral bias and the evolution of beliefs

The formulation of the exit problem discussed above indicates that delay can result if entrepreneur *i*'s belief about the probability he is operating a high-profit firm, P_{it}, is greater than the true probability conditional on the profits it has observed, P_t, and remains so in the face of noisy, but negative, information about performance. The literature on escalation of commitment, beginning with Staw (1976) and Staw and Ross (1978), identifies several behavioral biases that may prevent decision-makers' beliefs from evolving accurately.[7] In our context, these theories can best be interpreted via a Bayesian framework (consistent with equation (1) above), where the entrepreneur updates prior beliefs about the probability he operates a profitable firm with each new signal. To fix ideas, we represent this process with the following stylized model:

$$P_{it} = \alpha_i P_{i,t-1} + (1 - \alpha_i) S_t \quad (3)$$

where $P_{i,t-1}$ is the prior belief about the likelihood the venture is profitable, P_{it} is the posterior belief, S_t is the probability the venture is profitable based on profits observed in period *t* alone,

[4] Elfenbein and Knott (2013) highlight several predictions of the RL model for exit timing and test these predictions in the context of the U.S. banking industry between 1984 and 1997. They find empirical support for most of the model's main predictions.

[5] In our experiment, it is never optimal for high-profit firms to exit; therefore delay is only defined for unprofitable firms.

[6] We find it useful to refer to the difference in exit timing indicated by the Marshallian exit rule (i.e., smallest *t* where $P_t < \bar{p}$) and the RL model ($P_t < p^*$) as "rational delay."

[7] Escalation of commitment describes a class of phenomena sharing three features: investment toward a goal, repeated decisions in the face of negative feedback, and uncertainty about outcomes. The literature that seeks to explain escalation of commitment addresses a wider set of potential causal factors than we are able to address here.

and α_i is the weight placed by the entrepreneur on the prior.[8] Viewed from this perspective, some of the behavioral biases pertain to the *priors*; others pertain to interpretation of new information for *updating posteriors.*

Mechanisms affecting priors include the *sunk cost fallacy* (Thaler 1980)—the tendency to avoid losses from sunk investments despite their irrelevance, *anchoring* (Tversky and Kahneman 1974)—the tendency to rely too heavily on initial reference points, *status quo bias* (Samuelson and Zeckhauser 1988)—the tendency to maintain a behavior unless there is a compelling reason to change, and *overconfidence* (Roll 1986)—the tendency to overestimate one's own ability.[9] We assume that overconfidence manifests itself in upward bias of initial beliefs, P_0, whereas sunk cost fallacy, anchoring and status quo bias manifest themselves in over-weighting of prior beliefs, α, leading to a muted response to new information. Prior work suggests that overconfidence plays a significant role in entrepreneurial decision-making (e.g., Camerer and Lovallo 1999, Forbes 2005, Lowe and Ziedonis 2006, Wu and Knott 2006). Burmeister and Schade (2007) provide the only direct evidence that we are aware of on the role of status quo bias or other biases that generate muted responses to new information affect entrepreneurial decision-making.

In addition to the behavioral mechanisms affecting priors, are those affecting the accuracy of updating. These include *self-serving attribution bias* (Miller and Ross 1975)[10]—the tendency to treat successful outcomes to one's own skill and unsuccessful outcomes to bad luck, *confirmatory bias* (Lord, Ross and Lepper 1979)—the tendency to interpret information in a way that confirms preconceptions, and *motivated reasoning* (Kunda 1987)—the tendency to accept desirable information, but scrutinize or discard undesirable information. These mechanisms imply asymmetric updating (Eil and Rao 2011) in which managers place more weight on positive signals and less weight on negative signals. Operationally, we define a signal as positive if the likelihood of profitability implied by the new signal is better than expected, i.e., $S_t > P_{i,t-1}$, and

[8] Accurate Bayesian updating, of course, requires α to rise as more signals are accumulated, i.e., α should be a function of *t*. We address this in the analysis section below, but abstract away from it here to simplify the exposition.

[9] The terms overconfidence and optimism have multiple meanings in the extant literature. In some instances overconfidence refers to the accuracy of one's estimates (Fischoff, Slovic and Lichtenstein 1977); in others it refers to overestimating own ability. There is also similar confusion regarding optimism: optimism regarding outcomes generally (Heath and Tversky 1991), versus optimism about outcomes of own effort. We follow the convention that overconfidence refers to estimates of own ability.

[10] Note that in the experiment there is no opportunity to exercise skill other than through the exit decision—after which there are no profit updates. Thus any bias affecting updates will stem from confirmatory bias or motivated reasoning.

define it as negative when $S_t < P_{i,t-1}$. Asymmetric updating, then, implies modifying equation (3) to incorporate separate coefficients for positive and negative signals to allow for the presence of confirmatory bias and motivated reasoning, i.e.:

$$P_{it} = \{\alpha_i^+ P_{i,t-1} + (1-\alpha_i^+)S_t\} I_{[S_t > P_{i,t-1}]} + \{\alpha_i^- P_{i,t-1} + (1-\alpha_i^-)S_t\} I_{[S_t < P_{i,t-1}]} \tag{4}$$

Where $I_{[\cdot]}$ is an indicator variable that takes on the value 1 if the expression in brackets is true and 0 otherwise. To simplify equation (4) we defining $S'_{it} = S_t - P_{i,t-1}$, where the S'_{it} is difference between the signal at time t and its expected value. Further, we define $\beta_i^+ = 1 - \alpha_i^+$ and $\beta_i^- = 1 - \alpha_i^-$, respectively and rearrange yielding:

$$P_{it} - P_{i,t-1} = \left(\beta_i^+ I_{[S'_{it} > 0]} + \beta_i^- I_{[S'_{it} < 0]}\right) S'_{it} \tag{5}$$

In this expansion β_i^+ defines the relative sensitivity of the entrepreneur's belief when new information is better than expected and, β_i^- defines the relative sensitivity when it is worse than expected. Confirmatory bias and motivated reasoning imply that beliefs will rise more in the face of good news than they will decline in the face of bad news of the same magnitude, i.e., $\beta_i^+ > \beta_i^-$.[11] Differences in β_i's across groups (i.e., entrepreneurs and advisors) represent differential sensitivity to new information. Greater (lesser) muted response by entrepreneurs relative to advisors implies that the mean values of both β_i^+ and β_i^- would be lower (higher) for entrepreneurs than for advisors. Greater (lesser) asymmetric updating by entrepreneurs relative to advisors implies that mean values of the difference between positive and negative responses, $\beta_i^+ - \beta_i^-$, would be higher (lower) for entrepreneurs than for advisors.

3. Experimental Design

3.1 Overview

We develop an experiment that enables us to measure exit delay by individual decision-makers and to characterize its causes. We create an experimental market conforming to the RL model in which participants are provided complete information about the structure of the game, are allocated via chance to a firm of unknown type, and make decisions about whether to exit or remain in the market. The experiment includes both a treatment group and a control group. We call the treatment group entrepreneurs, because like entrepreneurs, they receive equity stakes (they earn the profits and losses for all periods they choose to remain in the market). Similarly

[11] This implies that greater weight will be placed on priors when news is bad, than when it is good ($\alpha_i^- > \alpha_i^+$).

their decisions mirror those of a new business founder who is unsure about his business' profitability and must determine whether and when to exit in order to maximize earnings. We gather data on entrepreneurs' exit decisions, as well as collect their beliefs each period regarding the probability that they have been assigned to a high-profit firm.

We compare the evolution of beliefs and exit decisions of entrepreneurs to those of a control group, labeled advisors. We included a control group because we had concerns that even rational decision-makers might not be able to optimize in accordance with the Ryan and Lippman model—either they may not internalize equation 1 in their updates, and/or they may be unable to identity the optimal exit threshold in equation (2).

Advisors and entrepreneurs receive identical information about the structure of the game, and receive identical profit signals each period. Advisors, however, are compensated only for their estimates each period about the probability they have been assigned to a high-profit firm. While we ask advisors for their recommendation about whether the firm should exit, we make it clear that this is a non-binding recommendation that will not affect their compensation. Thus the only distinction between entrepreneurs and advisors is that entrepreneurs receive equity stakes, whereas advisors do not.

3.2. Game parameters and optimal exit

We follow Ryan and Lippman (2003) in constructing profit streams from which participants must deduce their firm type and optimal exit time. All payoffs in the experiment are expressed in a fictional currency called eckels. The conversion rate between dollars and eckels is known by all participants.

Participants are allocated to one of two types of firms: high-profit (H) and low-profit (L), For all participants, the *ex ante* probability of being allocated to type H is 50%, corresponding to P_0 in RL. For type H firms, profits are drawn each round from a normal distribution with mean 200 eckels and standard deviation 50 eckels. For type L firms, profits are drawn from a normal distribution with mean 100 and standard deviation 50. Upon exit the firm receives a certain payout of 130 eckels (the "exit payout") for each remaining period in the game.[12] In the RL model, the values of μ_H, μ_L, and σ that correspond to these parameters are 70, –30, and 50,

[12] We chose to shift the RL parameters by +130 to avoid problems associated with loss aversion (Tversky and Kahneman 1991) and the possibility that participants might anticipate negative payouts. The optimal exit time defined by the RL model is completely invariant to this shift.

respectively. Additionally, we informed participants that in every period, there was a 10% chance the game would terminate in that period. This corresponds to a discount factor, δ, of 0.1. Equation (1), then, indicates that the optimal threshold for exit is when the posterior probability that a firm is type H falls below p* = 0.01915.[13]

Using these parameters, we randomly generated both type H and type L profit streams for two sets of games (four profit streams), which we label Game 1 and Game 2. We also allowed the length of the games to be determined stochastically: our random draws determined that the games that would terminate in periods 11 and 8, respectively. Table 1 shows the profit signals for type H and type L players in both games and additionally provides the evolving RL posterior estimate, P_t, computed each period using equation (1) from the market parameters, and the cumulative profit draws, X_t. In both games, the RL exit threshold is crossed in period 4 in the low profit condition.

Insert Table 1 about here

3.3. Procedure and Data Collection

The experiment was conducted at a public university in the central United States using z-Tree software (Fischbacher 2007). Participants were recruited via email from a pre-registered set of students who indicated a willingness to participate in economics laboratory experiments using ORSEE (Greiner 2004). The email simply informed potential participants that they would be paid for participating in the experiment, receiving a show-up fee plus compensation depending on their performance on an unspecified task and chance. Participants recruited for the entrepreneur sessions received a $5 show-up fee, while participants for the advisor sessions received an $8 show-up fee.[14] Overall, 66 participants were recruited for experimental sessions as entrepreneurs, and 67 participants were recruited as advisors.[15] Although we use the labels entrepreneur and advisor in this manuscript, to avoid expectancy effects, we refrained from using

[13] It is noteworthy that p* is significantly lower than $\overline{p}$ (which equals 0.30 for the experimental parameters). Thus, in our simulations the naïve exit points are significantly earlier than the optimal exit points.
[14] The higher show-up fees for the advisor sessions was requested by the Institutional Review Board to ensure that participants in these sessions were sufficiently compensated for their time.
[15] Participants were restricted from participating in both experiments.

these labels in any of the instructions provided to participants. Instructions simply provided information about the task, but did not identify roles.

Participants were seated in a large computer lab with screens to prevent participants from seeing others' terminals and work spaces. Prior to beginning the computer-based experimental task, an experiment facilitator announced to participants that they would participate in a study that examines decision-making. All instructions about the experiment, and all data collection, were provided through the participant's computer terminal.

Both entrepreneurs and advisors participated in Game 1 and Game 2 as shown in Table 1. In each game, advisors were assigned randomly with 50% being allocated to type H firms and 50% allocated to type L-type firms. The allocation in Game 1 was independent from the allocation in Game 2, so some advisors viewed profits only from type L firms, and some viewed profits only from type H firms. We examine the data for potential learning affects in the second round in the analysis that follows, but find no evidence of it.[16]

Extensive instructions were provided to participants about the task and their remuneration.[17] The first main page of instructions outlined the structure of the task, informed participants that their payoffs would be described in eckels, and provided the conversion rate between eckels and dollars.[18] The profit distributions of type H and type L firms were described in detail and were displayed graphically in each period, as was the exit payoff that entrepreneurs were to receive. The verbal and graphical descriptions of the profit distributions and exit payoffs were identical for both groups. In addition, entrepreneurs and advisors received identical instructions about the structure of the proper scoring rule that compensated them for providing their beliefs (Holt 2007: 384-385). We deemed these instructions to be complicated, so we added in bold text the phrase "you earn the most when your beliefs are as accurate as possible, and you

[16] In an attempt to manipulate their initial expectations, entrepreneurs were allocated to firms via two methods. In Game 1, half of entrepreneurs were allocated randomly to firms and split evenly between type H and type L. The other half of entrepreneurs were allocated via their performance on a 7-item quiz. Those who had an odd number of correct answers on the quiz were allocated to type L and the remainder to type H. In round 2, the allocation methods were reversed. Participants were informed when they were allocated via quiz and when they were allocated randomly. When allocated via quiz, participants were told that they would be allocated based on their performance on the quiz, with the constraint that half of respondents would be allocated to type H and type L firms. This manipulation had no effect on initial beliefs, so we don't discuss it further.

[17] Detailed screenshots for the experiment are available from the authors upon request.

[18] In entrepreneur sessions, the conversion rate between eckels and dollars was 250:1. For advisor sessions the conversion rate was 200:1. The slightly higher exchange rate for advisor sessions was requested by the IRB to ensure that participants in the advisor sessions would be sufficiently compensated for their time.

cannot do better than what you really believe your chances are of being a high-profit firm."[19] All participants were also required to provide their beliefs prior to receiving any profit signals; compensation via this proper scoring rule was also provided to elicit accurate initial beliefs.

After stating their beliefs in each period, entrepreneurs and advisors were then asked, respectively, whether they wanted to exit or to recommend exit. If in any period, a participant in the entrepreneur treatment chose exit, he received an exit payoff of 130 eckels for all remaining periods. Participants in the entrepreneur treatment who decided to exit were also required to provide a final assessment of their beliefs of being type-H, which was the basis of compensating them for belief reporting in all remaining periods of the game.[20] While participants in the advisor treatment were also asked each period whether they recommended exit, they were told explicitly these recommendations would neither affect the play of the game nor their payoffs. Moreover advisors continued to estimate probabilities and make exit recommendations in all periods of the game (including those beyond their first exit recommendation).

Table 2 summarizes the exit decisions made by all participants in the experiment, and Figure 1 shows the evolution of average beliefs for participants in the entrepreneur and advisor treatments, by condition, over the course of the experiment.

Insert Table 2 and Figure 1 about here

3.3.1. Demographic data

Once both rounds of the experimental task were completed, we collected additional information from the participants electronically. These data include demographic information such as age, gender, education, ethnicity, nationality, and language spoken in the home. A large fraction of participants were born outside of the United States, and more than half characterized themselves as Asian or South Asian. We view this diversity as strength of the data, as entrepreneurship rates among foreign born have been more than two times greater than rates

[19] For advisors the language was "the chances of them being a high-profit firm."

[20] To ensure that entrepreneurs' incentives to exit were not affected by their ability to be compensated for reporting their beliefs, we provided them with compensation for their beliefs for all remaining rounds of the game based on this last reported belief.

among US born in recent years (Fairlie 2012). Furthermore, it suggests that the results may be generalizable to international contexts.

This demographic data is summarized in Table 3, Panel A, and is broken down by participants in the entrepreneur and advisor treatments. None of the t-tests of parameter means rejects the null hypothesis that the two groups are equal. Thus the two groups are deemed equivalent in all respects other than the treatment—equity stakes and binding exit decisions.

3.3.2. Individual traits

In addition to the demographic data described above, we collected information about participants risk preferences, their attitudes toward uncertainty, fate, and decision-making, and asked them to answer a handful of questions about math and statistics. Risk preferences were measured by asking participants to accept $1 with certainty or one of five other 50-50 bets: $0.80/$1.40, $0.60/$1.80, $0.40/$2.20, $0.20/$2.60, or $0/$2.80. We code these choices from 1 to 6 where 1 represented the lowest risk and lowest expected reward, and 6 represented the highest risk and highest expected reward.[21] We label this variable *Risk Tolerance.* Participants next answered five math questions and three statistics questions; the statistics questions were quite challenging. We coded the variables *Math Score* and *Statistics Score* based on the number of responses that were correct. The mean values of these variables were 3.42 and 1.19, respectively. These scores were summed and z-scored to create a composite variable which we use in the analysis, *MathAndStatistics.* Finally, participants answered a number of questions about their attitudes towards making decisions or inferences under uncertainty and personal agency. These questions are provided in Table A1 in the Appendix. A principal components analysis revealed that these questions loaded onto four factors. The factor we label *Internal Locus of Control* consists of four questions regarding participants' beliefs about their control over their own fate or destiny. The factor *Control over Chance* consists of questions about whether participants prefer to call heads or tails in a coin flip and whether they believe that they are more likely to win if they do so. The factor we label *Quick Inference* combines scores on a series of questions about the participant's judgments about whether a deck of cards had been altered to remove all Aces. The variable *Knowledge Overconfidence* is the number of incorrect

[21] Choices 5 and 6 represented equal expected payoffs for the participants, but choice 6 clearly represents a greater appetite for risk.

scores in a task asking participants to create 90% confidence intervals for a series of 10 historical and scientific facts (Fischoff, Slovic, and Lichtenstein 1977). Table 3 Panel B presents the means of these variables for participants in the entrepreneur and advisor treatments. As with the demographic variables, all of the variable means are statistically indistinguishable from one another.

Insert Table 2 about here

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4. Analysis

Our analysis proceeds in five parts. We first compare entrepreneurs' exit decisions to the RL optimum and to the advisors' exit recommendations. Second, we explore the relationship between exit decisions / recommendations, and participants' beliefs. Third, we examine differences in exit thresholds across groups. Fourth, compare the evolution of beliefs between entrepreneurs and advisors and decompose the evolution of beliefs to explore potential sources of bias. Finally, we examine the relationship between individual characteristics, the evolution of beliefs, and their exit behavior.

4.1 Exit decisions of entrepreneurs and recommendations of advisors

Because exiting is never optimal in the high profit condition, we focus our analysis of exit decisions / recommendations of participants allocated to the low profit condition. Figure 2 provides the distribution of the exit decisions of entrepreneurs and the first exit recommendations of advisors relative to the optimal exit period. The median entrepreneur exits two periods after the optimum, and in more than one quarter of all cases, entrepreneurs reach the final period without exiting.[22] For advisors, the median delay (measured as the advisor's first exit recommendation) is -1. A t-test of whether the two groups exhibit the same delay is rejected with $p<0.001$ (t-statistic = -4.416, df = 69).

[22] For entrepreneurs, the median exit time is identical in both games, and a t-test of equality in exit time for entrepreneurs assigned to the low profit condition between games does not reject the null (t-statistic = 0.3473; p = .7294). Similarly, for advisors assigned to low profit condition, the difference in exit timing across games is also not significant (t-statistic = 0.0686; p = .9456). These tests suggest that potential learning effects between game 1 and game 2 in the experiment do not play a major role.

Insert Figure 2 about here

Figure 3 plots the Kaplan-Meier survival functions for entrepreneurs and advisors, respectively, where the failure event is the exit decision or first exit recommendation. A log-rank test of the equality of these survivor functions rejects the null hypothesis at $p < .0001$. Thus, there is very strong evidence that entrepreneurs exit later than advisors.

Insert Figure 3 about here

4.2. Impact of beliefs on exit

Marshall's theory of exit and the RL theory assume implicitly that actors' exit decisions are driven by their beliefs about being in a high-profit state. This foundational assumption is critical for us to claim that bias is a source of exit delay. Accordingly, Table 4 examines the relationship between beliefs and the hazard rate of exit for entrepreneurs using a Cox (1972) proportional hazard model. Contemporaneous profits are used as a control variable. Columns 1 – 4 examine behavior only in cases in which entrepreneurs are assigned to the low profit condition. Columns 5 and 6 examine pooled exit behavior for entrepreneurs in both high and low profit conditions. We report robust standard errors clustered by participant. The results are clear: the instantaneous hazard rate of exit is negative and significantly correlated with contemporaneous beliefs about the probability of being a high profit firm. Given the estimates in Column 1, a 10% decrease in the entrepreneur's belief about being a high-profit firm increases the odds of exit by 22%. Columns 2 through 4 incorporate initial beliefs and/or prior period beliefs. The models reveal that beliefs in $t-1$ are of the same sign, but much lower magnitude than the beliefs in t. Initial beliefs do not have a statistically significant impact on the hazard rate of exit. Overall this analysis confirms that beliefs drive exit.[23]

Insert Table 4 about here

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[23] Nearly identical results are obtained when performing the same analysis on advisors first exit recommendations.

4.3 Differences in exit thresholds

The prior sections document a significant and economically meaningful difference in delay between entrepreneurs and advisors, and further establish that exit decisions are driven by beliefs. We next seek to better understand the sources of relative delay across treatments. We begin by examining differences in exit thresholds. We define $ExitThreshold_{ig}$ as participant *i*'s belief about the probability they have been allocated to a high profit firm at the time they exit from game *g*. The average observed value of $ExitThreshold_{ig}$ for entrepreneurs is 0.184 (median 0.01) and for advisors 0.239 (median 0.15). The median $ExitThreshold_{ig}$ for entrepreneurs is relatively close to the RL exit threshold, $p^* = 0.019$, and median for advisors is near the midpoint between p^* and the Marshallian exit threshold, $\bar{p} = 0.30$.[24] A two-sample Wilcoxon rank-sum test of the equality of *ExitThreshold* across groups rejects the null hypothesis at p = .0075. Additionally, we estimate a regression of the form:

$$ExitThreshold_{ig} = \beta_0 + \beta_1 Entrepreneur_i + \tau_g + \gamma' X_i + \varepsilon_{it} \quad (6)$$

where *Entrepreneur* is an indicator variable that takes on the value 1 if the participant is in the entrepreneur treatment and 0 otherwise; τ_g is a game fixed effect; and the vector X_i includes demographic characteristics of participant *i*. We estimate a Tobit specification, to account for the fact that beliefs may not fall below 0, with standard errors clustered on participants to account for potential non-independence of these observations; we also estimate quantile (median) regressions with bootstrapped standard errors.

Table 5 presents the results of these estimations. In each estimation, $\hat{\beta}_1$ is negative and significant at the $p < .1$ level or below.[25] The estimates indicate that the exit thresholds of participants in the entrepreneur treatment are, on average, 10-14 percentage points below participants in the advisor treatment. In Table A2 in the appendix, we examine the robustness of these results using interval regressions, which enable us to account for the fact that we do not observe *ExitThreshold* for participants who do not exit (or recommend exit). These analyses are quantitatively similar to those reported in Table 5, and offer stronger statistical support. Together, they offer strong evidence that differences in exit between entrepreneurs and advisors can be partially explained by differences in exit thresholds. More importantly, they show that

[24] These values are computed using Equation 2 and the parameters chosen for the experiment.
[25] We make no attempt to correct for selection in these estimations as selection will bias the *Entrepreneur* coefficient upward, making it more difficult to support the hypothesis.

equity stakes improve decision-making in this setting insofar as they lead to exit thresholds that are closer to the RL optimum.

Insert Table 5 about here

4.4 Evolution of beliefs

Next we examine whether participants provided equity stakes form different beliefs than those without them. Figure 1 offers graphical evidence of the divergence of beliefs, but we examine these differences more formally here. We report the average beliefs of all players by condition and game in Appendix Table A3. The raw data indicate that in the low profit condition, the average beliefs of entrepreneurs exceed those of advisors in 16 out of 19 periods. To examine statistical significance and to account for the fact that we do not observe entrepreneurs' beliefs following exit, we perform a series of regressions in which we examine beliefs controlling for the condition and stage of the game, the participant's initial beliefs, and the participant's treatment (entrepreneur or advisor). We can also control for individual characteristics, although in principle the experimental design should approximate random assignment. In particular we estimate:

$$Belief_{itg} = \beta_0 + \beta_1 Belief_{i0g} + \beta_2 Entrepreneur_i + \tau_{itg} + \gamma' X_i + \varepsilon_{igt} \qquad (7)$$

where $Belief_{itg}$ is the belief of participant i in period t of game g, τ_{itg} are 38 fixed effects representing the interaction for each combination of game, period, and condition (high-profit or low profit), and *Entrepreneur* and X_i are defined as above. We examine Tobit specifications to allow for censoring of the dependent variable at 0 and 100, and report robust standard errors, clustered on participant.

Table 6 reports the results of this estimation. Columns 1 and 2 report result for the pooled sample and the low profit condition alone, without controls for participant characteristics. Columns 3 and 4 repeat the analysis including controls for participant characteristics. The results are clear. In each specification the coefficient on *Entrepreneur* is positive and significantly different from zero, although the level of significance depends on the sample and covariates. This suggests that the beliefs of participants in the entrepreneur treatment become higher than those in the advisor treatment, controlling for initial beliefs, once profit signals are received.

(The results remain when omitting initial beliefs from the estimation.) Columns 2 and 4 suggest that this overall divergence in beliefs across the two treatments is principally the result of divergence between entrepreneurs and advisors allocated to the low profit condition.

Insert Table 6 about here

To further understand the process by which beliefs are evolving, we estimate participants' Bayesian updating parameters from equation 4 using a random coefficients specification. This specification generates mean values and participant-specific errors for each coefficient. Since our interest is in overall patterns of Bayesian updating, we employ all data on beliefs from type H and type L firms in both games. We extend equation (8) to allow for attenuation in the strength of updating over time by incorporating polynomials of varying lengths to enter the updating equation. For each period *t*, we calculate S_{it} as the probability implied by equation (1) of actual earnings of the firm in period *t* if no prior information had been received. The independent variable, $\boldsymbol{S'_{it}}$, then, is the "news" for the participant, i.e., the difference between S_{it} and the belief in the prior period, $P_{i,t-1}$. As in (5) the dependent variable is the change in beliefs, $P_{it} - P_{it-1}$. Our estimation thus takes the form:

$$\boldsymbol{P_{it} - P_{i,t-1} = \left[(\beta^{+} + \beta_i^{+}) I_{[S'_{it}>0]} + (\beta^{-} + \beta_i^{-}) I_{[S'_{it}<0]} + p^{n}(t-1)\right] S'_{it} + \varepsilon_{it}} \qquad (7)$$

where $\boldsymbol{\beta^{+}}$ is the common effect of positive news on updates across all participants, and $\boldsymbol{\beta_i^{+}}$ is the idiosyncratic effect for subject *i*, and similarly for $\boldsymbol{\beta^{-}}$ and $\boldsymbol{\beta_i^{-}}$. The term $\boldsymbol{p^{n}(t-1)}$ represents an n^{th} order polynomial in *t-1*, allowing the influence of the signal to change over time.[26] We expect the influence of the signal to attenuate, as priors should become more precise as more performance information accumulates.

Table 7 presents the results of these estimations. Column 1 presents the parameter estimates with no time trend (n = 0), and columns 2, 3 and 4 present parameter estimates with linear, quadratic, and cubic time trends (n = 1, 2, and 3), respectively. Common parameter estimates are provided in Panel A. The results are clear and consistent across all models. In each specification, the estimated value of β^{+} exceeds the estimated value of β^{-} by 10 percentage points or more. These common parameter estimates suggest that participants as a whole engage

[26] Selection of *t-1* instead of *t* facilitates interpretation of the coefficients but does not alter the results.

in asymmetric updating—they change their beliefs more in the face of an increment of positive news than negative news. In the face of predominantly negative information (as in the low profit condition), this can lead to delay for both entrepreneurs and advisors, as beliefs for both groups do not adjust sufficiently in the face of "bad news."

The picture becomes clearer when we examine estimates of the total responsiveness of participants to positive and negative news, i.e, $\boldsymbol{\beta}^{+} + \boldsymbol{\beta}_{i}^{+}$ and $\boldsymbol{\beta}^{-} + \boldsymbol{\beta}_{i}^{-}$, and compare the results across the two treatments. For each specification, we provide the mean estimates of the random coefficient parameters by group and t-tests of the differences in these means in Panels B and C, respectively, of Table 7. The results are highly similar across each specification. In general, advisors and entrepreneurs respond nearly identically to positive news; the t-statistic comparing these means is less than 0.11 across all specifications. By contrast, advisors and entrepreneurs respond very differently to negative news. Entrepreneurs place roughly 9 percentage points less weight on bad news than advisors. These differences are significant at the $p < .05$ level, with t-statistics in excess of 2.03 across each specification. These estimates indicate that asymmetric updating is a significantly greater problem for entrepreneur than for advisors. Moreover, the fact that both groups have equivalent responses to positive information yields no support for predictions that anchoring or status quo bias play a role in exit delay. The principal sources of behavioral delay in this setting, then, likely stem from motivated reasoning and / or confirmatory bias induced by equity stakes rather than anchoring or status quo bias.

Insert Table 7 about here

4.5 Asymmetric updating, individual traits, and failure to exit

The preceding analysis suggests that differences in exit delay between entrepreneurs and advisors results from two sources: differences in exit thresholds and differences in sensitivity of beliefs to worse-than-expected information. Since the phenomenon that motivates our study is persistence of entrepreneurs in underperforming ventures, we now turn to an analysis of the link between asymmetric updating and failure of entrepreneurs to exit when assigned to low profit firms. We construct the dependent variable *Failure to Exit* as a dummy variable the equals 1 if the entrepreneur is assigned to the low profit condition but does not exit during the course of the game, and 0 otherwise. To measure individual-level asymmetric updating, we employ the estimates of the random coefficient model above using two alternative approaches: the difference between the strength of positive and negative updates, i.e. $(\beta^{+} + \beta_i^{+}) - (\beta^{-} + \beta_i^{-})$ and the ratio of the strength of positive to negative updates, i.e., $\frac{\beta^{+}+\beta_i^{+}}{\beta^{-}+\beta_i^{-}}$. For simplicity of exposition, we focus on coefficient estimates that come from model with a quadratic time trend; however, our results do not depend on which model's estimates we choose. Table A4 summarizes the data used for this analysis and presents a correlation matrix for the variables of interest.

We regress *Failure to Exit* on our measures of asymmetric updating, entrepreneurs' personal attributes, and a dummy variable that equals 1 if the observation comes from Game 2. Table 8 reports the results. In columns 1 and 2 we report estimates from a logit specification, and in columns 3 and 4 we report the marginal effect estimates from a probit specification. We report robust standard errors clustered on participant. In all specifications, the coefficients on our measures of asymmetric updating are positive and significant at the $p < .1$ level. This suggests that participants in the entrepreneur treatment who have greater relative responses to positive vs. negative news are more likely to fail to exit altogether. The estimates in column 3 suggest that a one standard deviation increase in asymmetric updating increases the likelihood of *Failure to Exit* by 10 percentage points.

Insert Table 8 about here

This analysis yields some further insight. We find that personal attributes are also linked to exit failure. In particular, those who score higher on *Internal Locus of Control* – individuals who believe that life events derive primarily from their own actions – are significantly less likely in the low profit condition to fail to exit altogether. By contrast, individuals who display higher levels of *Knowledge Overconfidence* are significantly more likely to fail to exit when assigned to the low profit condition. Similarly, those who score high on our measure of *Quick Inference* – individuals who draw conclusions based on less data – also are more likely to fail to exit. A potential explanation for this is that these individuals base their beliefs about their firm's prospects on a few early observations and then fail to incorporate new performance information as the experiment proceeds. Overall these correlations suggest that problems with updating beliefs extend beyond asymmetric updating, and that exit thresholds, essentially willingness to accept type I error, may be systematically related to personality traits. We view these relationships as fruitful areas for future research.

5. Discussion

Exit delay is an important problem for entrepreneurs as well as managers in a host of other settings. However it is not well understood. One reason for the limited understanding is that rational theories of delay and behavioral theories of delay both anticipate that delay increases with the magnitude of sunk cost and the degree of uncertainty. Accordingly it is difficult to disentangle the two forms of delay. Further within behavioral delay, there has been limited effort to isolate which of the numerous proposed mechanisms underpin it. Decomposing rational delay from behavioral delay and further isolating mechanisms underpinning behavioral delay are both necessary to address the real-world problem of delayed exit.

We attempted to address both issues by conducting a laboratory experiment for which optimal exit was well-defined and in which an entrepreneur group with equity stakes was compared to an advisor group whose compensation was based only on the quality of its assessment of the firm's prospects. We found that equity stakes induced both *rational delay* – the entrepreneurs' thresholds were closer to the rational exit threshold than advisors – and *behavioral delay* – entrepreneurs' beliefs were higher over the course of the game than advisors. Moreover, we found that while participants as a whole engage in asymmetric updating – placing more weight on positive information than negative information – equity incentives increased asymmetric updating. This suggests that incentives may exacerbate problems of motivated reasoning and confirmatory bias.[27] Finally, we find that long exit delays among entrepreneurs are a function of asymmetric updating and personality characteristics such as knowledge overconfidence and internal locus of control.

This research is not without limitations. First this is a lab experiment. While lab experiments have many advantages in allowing us to isolate the phenomena of interest, it may be difficult to extrapolate their results to the real world. Most notably, entrepreneurs are unlikely to know in advance the underlying distribution of profitability in their market. Second, our subjects are students, thus they may have different personality traits and decision-making capability than

[27] Campbell and Sedikes (1999) provide a meta-analysis of psychology experiments testing self-serving attribution bias and find that a number of factors moderate degree of bias, including task importance. Our results can be viewed as consistent with those prior results.

entrepreneurs. Accordingly we recommend complementing our study with conventional econometrics in real-world settings.

Nonetheless, our paper begins to open up the black box of exit delay and provides a number of implications. First, we find that sunk cost is *not* a necessary condition for exit delay despite its centrality in escalation of commitment (Staw 1976, Staw and Ross 1978) and in economic theory (Dixit 1989, Krugman 1989). Our entrepreneurs exhibit exit delay despite having neither entry costs nor exit costs. Second, standard models of economic behavior posit that individuals form beliefs based on the information they receive and then make utility-maximizing choices conditional on these beliefs, i.e., incentives affect behavior directly. Our experiment indicates that these models may be incomplete. In our setting, incentives affect beliefs as well as behavior. Designing appropriate managerial controls, then, involves recognizing both the direct and indirect effects of incentives.[28] Moreover, in the context of market entry, our results suggest entrepreneurs can't learn about their type in an unbiased fashion as is assumed in Jovanovic's (1982) model of noisy selection. That is likely one reason there is so much delayed exit. The very thing that motivates entrepreneurs (equity stakes) inhibits their learning.

Finally, our study highlights potential solutions to the problem of exit delay. One potential remedy is to provide decision-makers automated decision rules in settings where it is possible to identify parameters from the RL model. Since this is unlikely in most settings, a reasonable alternative may be to assign decision rights to parties without equity stakes or to use such parties as advisors to decision-makers with equity stakes. On average in the experiment, advisors exit recommendations were closer to the optimum in the low profit condition than entrepreneurs. Future research might examine whether there are variations on equity-based compensation that might be less susceptible to bias. A second approach is to recruit decision makers who are less susceptible to the behavioral biases associated with exit delay. Our results indicate that one way to accomplish this is to hire managers with low scores on knowledge overconfidence (a fairly easily administered instrument). Further research might examine whether this manipulation is effective in minimizing exit delay.

[28] This is different from the standard problems of multitasking (Holmstrom and Milgrom 1991) or imperfect alignment of performance measures with value (Baker 1992).

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Table 1. Game Parameters

Panel A: Game 1

	High-Profit Condition			Low Profit Condition		
Period	Payoff	Cumulative Average	P(High | Data, P_0 = 0.5)	Payoff	Cumulative Average	P(High | Data, P_0 = 0.5)
1	137.08	137.08	.37360317	128.05	128.05	.2935813055
2	276.51	206.80	.98947646	154.19	141.12	.3294858268
3	193.83	202.47	.99816100	117.10	133.11	.1164277870
4	96.35	175.94	.98449368	83.73	120.77	.0092164899
5	183.83	177.52	.99594709	149.70	126.55	.0091075542
6	180.20	177.97	.99878548	41.85	112.44	.0001214936
7	243.44	187.32	.99997104	41.53	102.31	.0000015861
8	183.76	186.88	.99999249	94.97	101.39	.0000001756
9	250.74	193.97	.99999986	99.62	101.19	.0000000234
10	160.98	190.67	.99999991	133.31	104.41	.0000000120
11	247.40	195.83	.99999999	60.83	100.44	.0000000003

Panel B: Game 2

	High-Profit Condition			Low-Profit Condition		
Period	Payoff	Cumulative Average	P(High | Data, P_0 = 0.5)	Payoff	Cumulative Average	P(High | Data, P_0 = 0.5)
1	250.36	250.36	.982269706	115.36	115.36	.2000994709
2	224.39	237.38	.999079807	171.85	143.61	.3748050370
3	215.17	229.97	.999932071	105.74	130.98	.0926268289
4	223.40	228.33	.999996394	87.92	120.22	.0084493964
5	132.68	209.20	.999992789	126.52	121.48	.0033202978
6	304.28	225.05	.999999985	91.92	116.55	.0003262541
7	185.78	219.44	.999999996	98.89	114.03	.0000422409
8	126.01	207.76	.999999991	49.50	105.96	.0000007585

Table 2. Summary of Game Play

Panel A: Game 1

	High-Profit Condition			Low Profit Condition		
Period	Player Exits	Advisor 1st Exit Rec.	Advisors Recommending Exit	Player Exits	Advisor 1st Exits	Advisors Recommending Exit
1	1	7	20.0%	4	8	25.0%
2	1	0	2.9%	1	1	10.0%
3	0	3	8.6%	3	9	43.8%
4	0	7	28.6%	5	8	71.9%
5	1	2	5.7%	1	1	21.9%
6	0	1	20.0%	6	2	78.1%
7	0	0	0.0%	5	2	81.3%
8	0	0	11.4%	1	0	71.9%
9	0	0	0.0%	1	0	71.9%
10	0	0	17.1%	1	0	37.5%
11	0	0	8.6%	0	0	87.5%
No Exit	24	15	57.1%	11	1	96.8%
N	27	35		39	32	

Panel B: Game 2

	High-Profit Condition			Low-Profit Condition		
Period	Player Exits	Advisor 1st Exit Rec.	Advisors Recommending Exit	Player Exits	Advisor 1st Exits	Advisors Recommending Exit
1	0	3	9.4%	0	14	40.0%
2	0	0	3.1%	0	2	14.3%
3	0	0	3.1%	0	1	37.1%
4	0	0	3.1%	6	9	71.4%
5	1	5	25.0%	3	1	42.9%
6	0	0	0.0%	13	3	77.1%
7	0	0	15.6%	2	0	74.3%
8	0	3	31.3%	3	1	82.9%
No Exit	27	21	34.3%	11	4	88.6%
N	28	32		38	35	

Table 3. Summary Statistics for Survey – All Participants

Panel A: Demographic characteristics

	Entrepreneurs			Advisors		
	Obs.	Mean	St Dev.	Obs	Mean	St Dev
Male	66	.652	.480	67	.582	.496
Age	66	22.1	2.06	67	22.4	2.36
US Born	66	.212	.411	67	.253	.438
Other Language	66	.772	.417	67	.836	.373
Grad Student	66	.493	.503	67	.507	.503

Panel B: Participant Attributes

	Entrepreneurs			Advisors		
	Obs.	Mean	St Dev.	Obs	Mean	St Dev
Risk Tolerance *(1 = low risk / lowest expected value, 6 = highest risk / highest expected value)*	66	3.89	1.75	67	3.81	1.86
Knowledge Overconfidence	66	-.076	1.02	67	.075	.987
Internal Locus of Control	66	-.081	1.05	67	.109	.974
Control over Chance	66	-.077	.467	67	.070	.554
Quick Inference	66	.016	1.02	67	-.087	1.00
Math and Statistics	66	.065	1.02	67	-.113	.926

Panel C: Initial Beliefs

	Entrepreneurs			Advisors		
	Obs.	Mean	St Dev.	Obs	Mean	St Dev
Belief about Type = H before start of game	132	68.2	21.3	134	68.9	22.4

Note: See Appendix A1 for breakdown of the individual questions use to construction of participant attributes measures in Panel B.

Table 4. Validating the Importance of Beliefs—Cox Hazard Rate Analysis

	(1)	(2)	(3)	(4)	(5)	(6)
Variables:						
$Profit_t$	-.00591	.00214	.00593	.00585	-.00957***	-.00929***
	(.00541)	(.00566)	(.00542)	(.00550)	(.00298)	(.00290)
$Belief_t$	-.0196***		-.0196***	-.0167***	-.0231***	-.0184***
	(.00622)		(.00622)	(.00597)	(.00596)	(.00557)
$Belief_{t-1}$				-.00681*		-.00920**
				(.00388)		(.00395)
Initial Belief		-.00138	-.000215		-.00243	
		(.00611)	(.00546)		(.00547)	
N	77	77	77	77	132	132
Failures	55	55	55	55	59	59
Time at Risk	502	502	502	502	995	995
Log-pseudolikelihood	-209.4	-216.3	-209.4	-208.4	-242.2	-240.5
Wald chi-sq	11.21	.017	11.30	12.85	42.55	40.33
Prob > chi-sq	.004	.919	.010	.005	.000	.000

Note: The implicit dependent variable is the hazard rate of exit. Robust Standard Errors, clustered on participant in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$ (two-sided test). Coefficients displayed. Positive values indicate greater hazard rates of exit.

Table 5. Comparison of Beliefs at Time of Exit

Specification:	Tobit			Quantile (Median) Regression		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables:						
Entrepreneur	-14.09*	-14.04*	-13.35*	-14***	-10**	-9.444**
	(8.327)	(8.304)	(7.761)	(5.173)	(4.738)	(3.470)
Game 2		-8.264	-8.975*		-9*	-5.556
		(5.143)	(5.000)		(5.070)	(3.988)
Constant	19.66***	23.43***	59.52	15***	20***	23.89
	(4.457)	(5.062)	(54.43)	(4.235)	(4.867)	(23.24)
σ	38.20***	37.99***	36.68***			
	(4.419)	(4.394)	(4.089)			
Participant chars.	N	N	Y	N	N	Y
N	152	152	152	152	152	152
Pseudo-R^2	0.004	0.005	0.014	.024	.035	.060
F-Statistic	2.863	2.779	1.762	-	-	-
Prob > F	0.093	0.065	0.099	-	-	-

Note: The dependent variable is the participant's belief about the probability it is a high-profit firm at the time of exit (entrepreneurs) or at time of first exit recommendation (advisors). Columns 1 – 3 report the estimates from a Tobit specification with a lower limit of zero and robust standard errors clustered on participant in parentheses. Columns 4 – 6 report the estimates from a quantile (median) regression with bootstrapped standard errors (100 repetitions) in parentheses. *** p < 0.01; ** p < 0.05; * p < 0.1 (two-sided test).

Table 6. Tobit Analysis Comparing of Entrepreneur and Advisor Beliefs

	(1)	(2)	(3)	(4)
Variables:				
Entrepreneur	7.239**	10.629*	6.660*	11.311**
	(3.658)	(5.687)	(3.436)	(4.987)
Initial Belief	.135	.299**	.106	.160
	(.091)	(.142)	(.097)	(.136)
Game-Period-Condition F.E.	Y	Y	Y	Y
Participant Characteristics	N	N	Y	Y
Condition	High & Low	Low Only	High & Low	Low only
N	2,268	1,134	2,268	1,134
Pseudo-R^2	.0774	.0340	.0791	.0423
Log pseudolikelihood	-8412.8	-4416.9	-8397.7	-4378.5
F-Statistic	15.50	15.38	15.20	14.47
Prob > F	.000	.000	.000	.000

Note: The dependent variable is the participant's belief about the probability it is a high-profit firm. Robust standard errors clustered on participant in parentheses. Constant term and σ not reported. *** p < 0.01; ** p < 0.05; * p < 0.1 (two-sided test).

Table 7. Random coefficients estimates of responsiveness to new information

Time trend:	None	Linear	Quadratic	Cubic
	(1)	(2)	(3)	(4)
Panel A: Common parameter estimates and model statistics				
Parameters:				
β^+	0.5884	0.6252	0.6832	0.6457
	(0.0414)	(0.0444)	(0.0467)	(0.0500)
β^-	0.4719	0.5112	0.5809	0.5462
	(0.0338)	(0.0377)	(0.0419)	(0.0450)
(t-1)		-0.0114	-0.0623	-0.0040
		(0.0049	(0.0148)	(0.0318)
$(t-1)^2$			0.0058	-0.0107
			(0.0016)	(0.0081)
$(t-1)^3$				0.0012
				(0.0006)
Random effects				
$\sigma(\beta^+)$	0.3197	0.3184	0.3095	0.3083
	(0.0386)	(0.0383)	(0.0380)	(0.0379)
$\sigma(\beta^-)$	0.3194	0.3194	0.3060	0.3038
	(0.0289)	(0.0289)	(0.0286)	(0.0286)
Observations	2268	2268	2268	2268
Groups	133	133	133	133
Log-likelihood	-10770	-10768	-10762	-10759
Wald chi-sq	396.6	408.1	432.9	440.1
Panel B: Mean parameter estimates: Advisors vs. Entrepreneurs				
$\mu_{advisors}(\beta^+ + \beta_i^+)$	0.5892	0.6273	0.6847	0.6472
	(0.0299)	(0.0298)	(0.0287)	(0.0285)
$\mu_{entrepreneurs}(\beta^+ + \beta_i^+)$	0.5877	0.6232	0.6818	0.6443
	(0.0223)	(0.0220)	(0.0213)	(0.0212)
$\mu_{advisors}(\beta^- + \beta_i^-)$	0.5174	0.5565	0.6252	0.5890
	(0.0340)	(0.0331)	(0.0323)	(0.0320)
$\mu_{entrepreneurs}(\beta^- + \beta_i^-)$	0.4257	0.4652	0.5361	0.5028
	(0.0294)	(0.0285)	(0.0277)	(0.0275)
Panel C: Comparison of means across groups (t-statistics)				
Response to positive information (A vs. E): $\mu_{adv}(\beta^+ + \beta_i^+)$ - $\mu_{ent}(\beta^+ + \beta_i^+)$ *(df= 131)*	0.0395	0.1097	0.0794	0.0799
Response to negative information (A vs. E): $\mu_{adv}(\beta^- + \beta_i^-)$ - $\mu_{ent.}(\beta^- + \beta_i^-)$ *(df= 131)*	2.0385	2.0862	2.0924	2.0424
Advisors (positive vs. negative) $\mu_{adv}(\beta^+ + \beta_i^+)$ - $\mu_{adv}(\beta^- + \beta_i^-)$ *(df= 66)*	1.9230	1.9507	1.7172	1.6895
Entrepreneurs (positive vs. negative) $\mu_{ent}(\beta^+ + \beta_i^+)$ - $\mu_{ent.}(\beta^- + \beta_i^-)$ *(df= 65)*	4.6531	4.6594	4.4708	4.3685

Notes: The dependent variable is the change in beliefs from period t-1 to period 1. Standard errors in parentheses.

Table 8. Asymmetric Updating, Personality Characteristics, and Failure to Exit among Participants in Entrepreneur Treatment

Specification	Logit		Probit (marginal effects)	
	(1)	(2)	(3)	(4)
Variables:				
Difference in Strength of Response to Positive vs. Negative News	2.5039*		0.3588*	
	(1.4853)		(0.2068)	
Ratio of Strength of Response to Positive vs. Negative News		0.8650*		0.1263*
		(0.4826)		(0.0687)
Math And Statistics	0.3436	0.2073	0.0471	0.0297
	(0.3992)	(0.3883)	(0.0560)	(0.0552)
Risk Tolerance	0.0095	0.0656	0.0047	0.0109
	(0.2157)	(0.2091)	(0.0304)	(0.0298)
Internal Locus of Control	-0.6182**	-0.6077**	-0.0970**	-0.0941**
	(0.2835)	(0.2810)	(0.0484)	(0.0454)
Control over Chance	0.9511	0.9267	0.1422	0.1393
	(0.7029)	(0.6958)	(0.0985)	(0.0983)
Quick Inference	0.9071**	0.9513**	0.1381***	0.1422***
	(0.3846)	(0.3909)	(0.0493)	(0.0486)
Knowledge Overconfidence	1.5711***	1.5937***	0.2398***	0.2410***
	(0.4459)	(0.4335)	(0.0660)	(0.0657)
Round	0.4735	0.4850	0.0626	0.0672
	(0.7677)	(0.7726)	(0.1039)	(0.1038)
Observations	77	77	77	77
Log Pseudolikelihood	-29.70	-29.81	-29.33	-29.39
Pseudo-R^2	0.355	0.353	0.363	0.362
Chi-2	27.37	28.89	31.95	33.13
Prob > Chi-2	0.0006	0.0003	.0001	.0001

Figure 1. Average Beliefs of Entrepreneurs and Advisors

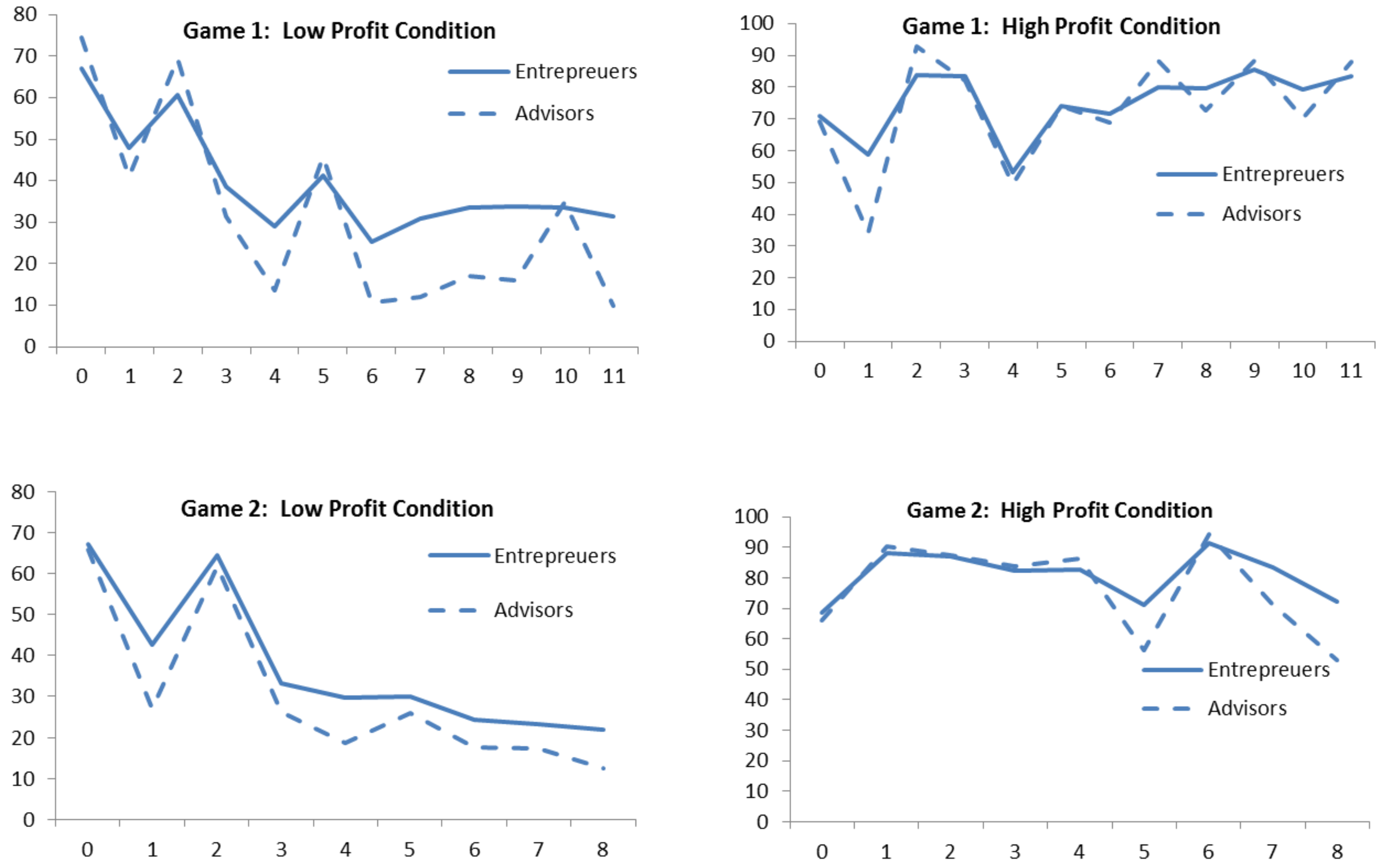

Figure 2. Comparison of Exit Delay between Entrepreneurs and Advisors, firm type L

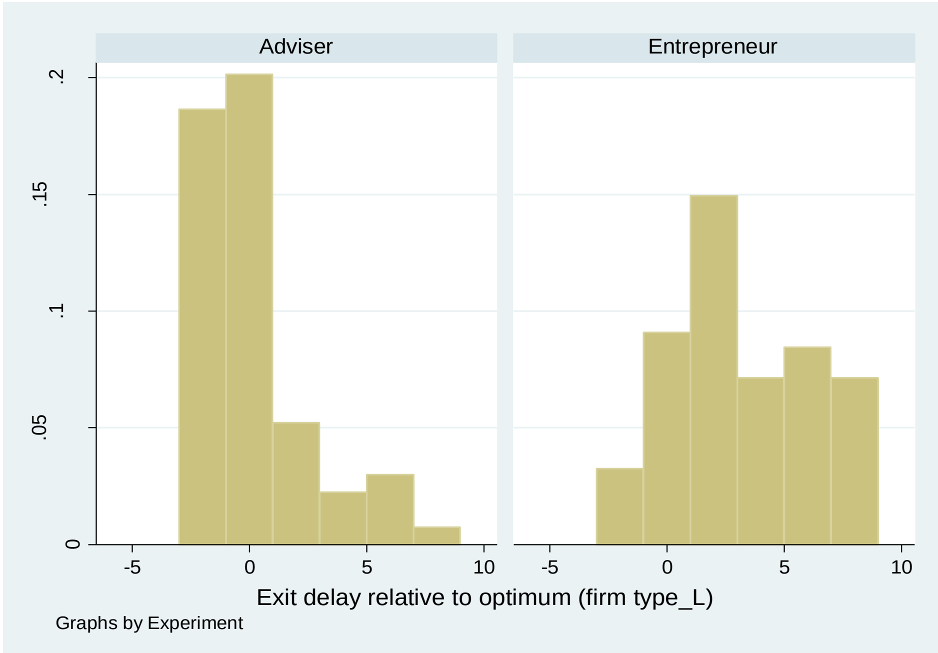

Figure 3. Comparison of Exit Delay between Entrepreneurs and Advisors, firm type L

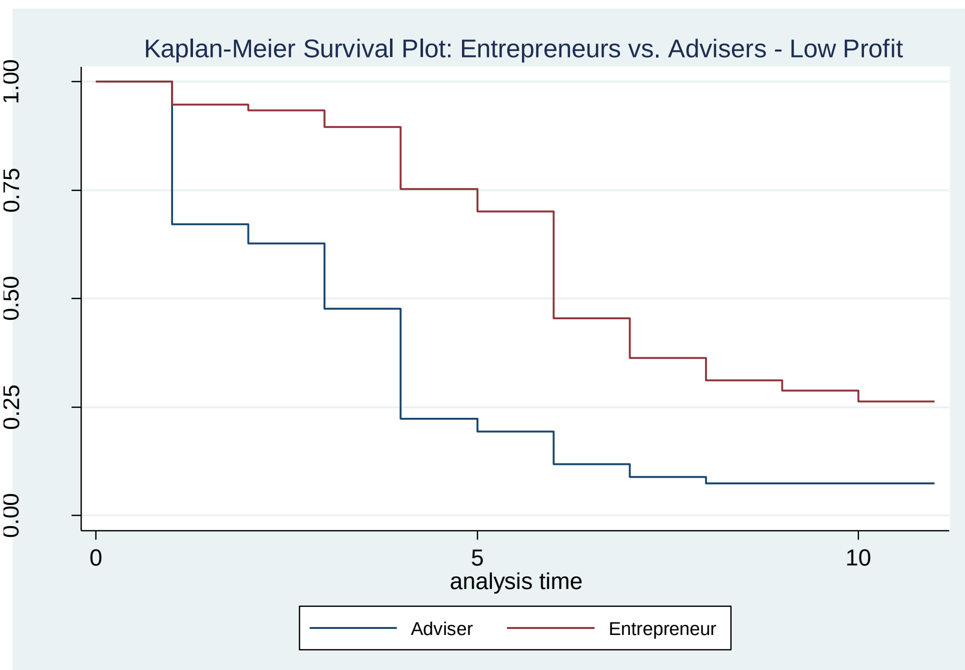

Table A1. Survey Questions

	Entrepreneurs			Advisors		
Health *(1 = Excellent, 5 = Poor)*	66	1.70	.744	67	1.72	.831
Get Deserve *(1 = Always, 5 = Never)*	66	2.54	.768	67	2.40	.740
Fate (*1 = Everything Determined by Fate, 10 = -People shape fate themselves)*	66	7.10	2.28	67	7.60	1.91
Freedom of Choice and Control over Life *(1 = No choice at all, 10 = A great deal of choice)*	66	7.50	2.02	67	7.72	1.61
Prepared to Take Risks? *(1 = Avoid, 10 = Prepared for Risk)*	66	6.88	2.13	67	6.88	2.12
Math questions correct *(out of 5)*	66	3.42	1.28	67	3.42	1.21
Statistics questions correct *(out of 3)*	66	1.06	.909	67	1.33	.990
Luck – ability *(1 = all luck, 7 = all skill)*	66	4.84	1.41			
Luck – random *(1 = all luck, 7 = all skill)*	66	3.03	1.52			
Coinflip: prefer own choice *(1 = Yes, 0 = No)*	66	.515	.503	67	.433	.499
Coinflip: prefer opponent choose *(1 = Yes; 0 = No)*	66	.121	.329	67	.134	.343
Coinflip: prefer random *(1 = Yes; 0 = No)*	66	.363	.485	67	.433	.499
Coinwintoss: *(1 = I am more likely to win if I flip the coin myself; 0 = same chance to win)*	66	.409	.495	67	.267	.446
Confidence Interval Score *(0 = all true values lie outside 90% confidence intervals; 10 = no true values lie outside confidence 90% intervals)*	66	2.85	2.09	67	2.54	2.02
Risk Choice *(1 = low risk / lowest expected value, 6 = highest risk / highest expected value)*	66	3.89	1.75	67	3.81	1.86
Altered Deck Belief After 5 Cards	66	42.3	22.9	67	42.8	25.8
Altered Deck Belief After 10 Cards	66	53.0	25.0	67	49.7	24.8
Minimum Cards	66	24.4	14.1	67	26.9	15.2

Table A2. Comparison of Beliefs at Time of Exit

Specification:	Interval Regression		
	(1)	(2)	(3)
<u>Variables:</u>			
Entrepreneur	-14.169***	-14.141***	-12.47**
	(5.282)	(5.296)	(5.122)
Game 2		-3.855	-3.846
		(3.193)	(3.220)
Participant chars.	N	N	Y
N	266	266	266
Left-Censored Obs.	114	114	114
Log pseudolikelihood	-763.2	-762.7	-754.7
Wald-Chi2	7.20	9.35	20.03
Prob > F	.007	.009	.067

Note: The dependent variable is an interval that takes the value [. , 0] if the belief is 0 at the time of exit, [$belief_{exit}$, $belief_{exit}$] if $belief_t$ is between 0 and 100 at the time of exit, and [. , $min_t\{belief_t\}$] if the participant does not exit or recommend exit. Constant term and σ not reported Robust standard errors clustered on participant in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$ (two-sided test).

Table A3. Evolution of Beliefs – Low Profit Condition

Panel A: Game 1

Period	Advisor	Entrepreneur	Difference Entrepreneur – Advisor	t-stat*
Before Start	74.5	67.1	-7.4	-1.52
1	41.1	48.0	6.8	1.00
2	69.5	60.7	-8.8	-1.43
3	31.3	38.7	7.5	1.03
4	13.7	29.1	15.4**	2.43
5	45.8	41.2	-4.7	-0.60
6	10.7	25.2	14.5**	2.11
7	12.0	30.8	18.8**	2.27
8	17.1	33.4	16.3**	2.23
9	16.1	33.9	17.8**	2.35
10	34.8	33.6	-1.2	-0.01
11	9.9	31.5	21.6***	3.31
N	32	39		

Panel B: Game 2

Period	Advisor	Entrepreneur	Difference Entrepreneur – Advisor	t-stat*
Before Start	65.7	67.1	1.34	0.25
1	27.0	42.7	15.68**	2.31
2	61.7	64.5	2.78	0.42
3	26.3	33.2	6.84	0.99
4	18.7	29.7	10.94	1.50
5	25.9	29.9	4.04	0.55
6	17.7	24.4	6.74	0.90
7	17.4	23.2	5.81	0.80
8	12.4	21.9	9.49	1.30
	35	38		

[1]t-stat is from equal variance t-test. *** p < .01; ** p < .05; * p < .1 (two-sided test)

Table A4. Failure to exit, Asymmetric Updating, and Personality Characteristics: Summary Statistics

#	Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9
1	Failure to Exit	.285	.454	--								
2	Initial Belief	67.05	21.63	.020	--							
3	Difference in Pos vs. Neg response	.121	.261	.199	.008	--						
4	Ratio of Pos. vs. Neg response	1.445	.766	.196	.067	.875	--					
5	Math and Statistics	-.117	.909	-.044	.112	-.111	-.037	--				
6	Internal Locus of Control	-.132	.976	-.022	.090	.076	.054	.178	--			
7	Control over Chance	.043	.551	.297	.164	.136	.142	-.198	-.115	--		
8	Quick Inference	.014	1.024	.209	-.010	.005	.053	.050	.089	.132	--	
9	Knowledge Overconfidence	-.119	.981	.410	.155	-.010	-.015	-.079	-.102	.115	-.051	--
10	Risk Tolerance	3.974	1.77	-.121	.088	.033	-.015	.190	.178	-.162	-.235	-.146