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CASH-OUT OR FLAME-OUT! OPPORTUNITY COST AND ENTREPRENEURIAL STRATEGY: THEORY, AND EVIDENCE FROM THE INFORMATION SECURITY INDUSTRY

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ABSTRACT

We analyze how entrepreneurial opportunity cost conditions performance. We depart from the literature on entrepreneurship which identifies survival with performance. Instead, many entrepreneurs aim for a cash-out (IPO or acquisition), especially in innovation based industries. Striving for a cash-out makes mistakes more likely and increases the probability of failure. High opportunity cost entrepreneurs will attempt to cash-out (IPO or friendly acquisition) quickly, even if it implies a higher risk of failure. Entrepreneurs with fewer outside alternatives may tend to linger on longer. We formalize this intuition with a simple model. Using a novel dataset of information security startups we find that entrepreneurs with high opportunity costs are not only more likely to cash-out but they are also more likely to fail. As well, our results confirm the predicted role of venture quality in conditioning the relationship between entrepreneurial opportunity cost and entrepreneurial performance.

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1 Introduction

There is a significant difference between opening a new restaurant, a consultancy, or even a car dealership, on the one hand, and starting a high-tech firm on the other. This difference is widely appreciated by scholars yet some of the implications are not as widely appreciated.[2] For instance, firm survival is frequently used as a measure of performance. Survivors are assumed to be superior performers, and, conversely, firms that leave the industry are treated as failures. But whereas a dry-cleaning store owner probably aspires to a steady flow of income, a modern high tech-entrepreneur may happily settle for a large payout after being acquired by an established incumbent. Unlike the "steady as she goes" approach of the dry-cleaner, the modern high-tech startup may often go for broke in trying for a big payout. While this is a difference of degree rather than kind, we believe that the difference is large enough to be consequential for the study of entrepreneurship.[3]

Many entrepreneurs are very accomplished and have significant outside opportunities. These high opportunity cost entrepreneurs are interested in ventures with substantial "upside" potential. If this potential is not quickly realized, they may prefer to leave and try their hand at something else (including perhaps a different startup), rather than linger on in a venture with modest prospects. Survival for such entrepreneurs is rarely a goal.

This type of entrepreneurship motivates our paper. We distinguish between two possible outcomes for a startup. It can either fail (e.g., if is dissolved and its assets are acquired), or it can cash-out (have an IPO or be acquired on favorable terms). Both of these outcomes are treated as "absorbing states"; if neither happens, the firm merely survives for another period. We depart

[2] This distinction is sometimes mirrored in studies of entrepreneurship, with broad based studies using "self employment" as a measure of entrepreneurship (e.g Hamilton, 2000), and more focused, industry cases studies directly observing firm formation (e.g., Klepper, 2002)

[3] Of course, not all ventures in technology intensive industries are alike. An IT consultancy or a firm with a niche software product is quite different from the prototypical Silicon Valley startups.

from the literature by treating survival (without an IPO) as not desirable in itself. Instead, survival merely keeps alive the option of trying for a payday. However, the option of waiting is more costly for entrepreneurs with higher opportunity cost and thus, higher opportunity cost entrepreneurs are more likely to undertake strategies that increase the likelihood of cash-out even if that entails a higher probability of failure.

We develop a simple model formalizes this intuition. In our model, each startup or venture is characterized by a quality level. In any period, the entrepreneur can undertake costly actions, hereafter called "investment", that increase the probability of a cash-out. But since "haste makes waste", striving for a cash-out can also increase the risk of failure. The firm may run out of cash, may scale up too quickly and make mistakes in product design or market positioning, or hire the wrong people. Thus, in our model, increasing the investment increases the probability of a cash-out but also increases the probability of failure. If the firm does not cash-out and does not fail either, it survives to try again. All else equal, an entrepreneur with a higher opportunity cost will value the option embodied in survival less than an entrepreneur with lower opportunity cost, and accordingly, will invest more. This results in higher hazards of both cash-out and survival.[4]

We test this intuition using a novel hand collected dataset of startups that entered the information security market (ISM) from 1989 through 2004. This paper is organized as follows. The following section provides a brief overview of the literature. In section 3, we develop a formal model and develop testable implications. In section 4, we explain the data sources for our

[4] The investment made by the startup is analogous to the real world concept of "burn rate". Increasing the burn rate makes it more likely that a firm with an underlying good idea will attract attention and capital. It also increases the likelihood that the firm will run out of cash and go under. Adding a cash constraint would not, we conjecture, change our results.

empirical analysis. Section 5 contains the results of the empirical analysis. We conclude in section 6, with a discussion of the implications and possible extensions.

2 Literature and background

Our paper builds on several streams of entrepreneurship research. The first stream examines the role of entrepreneurial opportunity cost. Much of the research has focused on how opportunity cost conditions selection into self-employment. The decision of an entrepreneur to exploit an entrepreneurial opportunity depends on whether the expected value of entrepreneurial profit is large enough to compensate for the opportunity cost of other alternatives (Shane and Venkataraman, 2000). Amit, Muller, and Cockburn, (1995) show that entrepreneurs with higher opportunity costs are less likely to select into entrepreneurship.

In addition, several scholars have pointed out that higher opportunity cost will also trigger exit. For instance, Gimeno et al. (1997) estimate a model of entrepreneurial performance where entrepreneurial human capital increases both the quality of the enterprise as well as opportunity cost, and increases the likelihood of exit. Their sample is a broad cross section across a range of sectors. We focus on a single industry and control for different sub-segments as well. Gimeno et al. use a self reported measure of "money taken out" per year as a measure of performance, we use cash-out. The Gimeno et al. measure proxies for viability whereas our measure proxies for a substantial potential upside. Further, Gimeno et al try to separately measure specific and general human capital, with the former driving performance and the latter driving opportunity cost. We use work experience to measure opportunity cost, and separately control for whether the founder had worked in a related or unrelated sector. We control for quality using patents, trademarks, and most importantly, use the initial size of the venture as a summary measure of quality.

As we do in our model, Bates, (2005) distinguishes between exit and success. In a study of small businesses created between 1989 and 1992, and then closed down between 1993 and 1996, he finds that owners often described their firms as "successful" when the closure decision was made. Moreover, he finds that highly educated and skilled owners were more likely move to other lines of work in many successful closure situations. In Bates's study, success is a subjective assessment by the entrepreneur, whereas we equate it with an IPO or favorable acquisition.

That high opportunity cost entrepreneurs are more likely to cash-out but also more likely to fail links to two additional strands in the literature. First, it points to the potential confounding effect of measures of opportunity cost and measures of human capital, and more broadly, of the quality of the venture. There is a large literature that links entrepreneurial performance to entrepreneurial experience. Broadly, it finds pre-entry experience is valuable and improves performance, although there is less clarity on what types of experience is valuable and how it improves performance. Much, though not all, of this literature uses survival as a measure of performance. For instance, startups from related parents survived longer in automobiles (Klepper, 2002) and shipbuilding industries Thompson, (2005). In lasers, spinoffs survived longer due to technical and manufacturing experience that the founders had accumulated while working for the parent (Klepper and Sleeper, 2005).

Another reason to control for quality is that, as already noted, entrepreneurial opportunity cost also conditions selection into entrepreneurship. All else constant, a high opportunity cost entrepreneur will only enter if she believes the prospects of success to be high enough. This implies that venture quality would be correlated with entrepreneurial opportunity cost. We distinguish between quality and opportunity cost. Following the literature, we measure opportunity cost by the pre-entry experience of the entrepreneur, but independently control for the quality of the startup. We control for the quality of the venture by the initial size. There is a significant literature which holds that more capable entrepreneurs start larger firms. For instance, Jovanic's classic 1982 paper shows that more able entrepreneurs start larger firms. Similarly, Cressy (2006) provides a model in which more able entrepreneurs start larger firms and are less likely to fail. The empirical evidence supports this theoretical finding (cf. Mata and Portugal, 1994; Agarwal and Audretsch, 2001). Colombo et al. (2004) find that in a sample of 391 young Italian high-tech firms, industry-specific professional knowledge and managerial and entrepreneurial experiences was associated with initial firm size. Cassar, (2006) found that among prospective entrepreneurs, more experienced ones intended to start larger firms and to grow more rapidly. In addition, industry studies show that initial firm size is highly correlated with firm performance, albeit typically measured as survival (Evans 1987a and 1987b; Dunne, et al. 1988 and 1989; Phillips and Kirchhoff, 1989; Audretsch, 1991; Audretsch and Mahmood, 1994 and 1995; Mata et al. 1995; Audretsch, 1995b; Cabral and Mata, 2003).

In our analysis we follow Heckman and Singer (1984) to further allow for unobserved heterogeneity in quality across firms. Finally, as a robustness check, we also use variation in macroeconomic conditions to identify the effect of opportunity cost. Boden and Nucci, (2000) find that small business founded when the economy is weak tend to have more educated, more experienced, and specifically had greater managerial experience, than those founded in better economic times. Consistent with this, we find that firms founded shortly after the Internet bubble burst, have lower hazards of failure and cash-out. Since we control for starting size and pre-entry experience, this is consistent with the conjecture that the bursting of the Internet bubble reduced opportunity cost of entrepreneurship. Note that if this had merely reduced the likelihood of a successful IPO, there is no reason to expect a decrease in failure rates. Instead, we find that this cohort had lower failure rates as well.

A second potential link is with the literature on entrepreneurial optimism (and over-optimism). The literature on entrepreneurial optimism is extensive. Broadly, it finds that entrepreneurs tend to be optimistic than the general population (e.g., Cooper, Woo, and Dunkelberg, 1988). This over-optimism or perhaps hubris is typically believed to result in higher failure rates, although the causal mechanisms and empirical evidences are far from clear (Camerer and Lovallo, 1999; Hayward et al., 2006).[5] De Meza and Southey, (1996) note that in the presence of financing constraints, more optimistic individuals select into entrepreneurship, and in the presence of financing constraints, may enter at low initial scale. Fraser and Greene, (2006), find empirical support for the idea that more optimistic entrepreneurs start larger firms. Hmieleski and Baron, (2009) find that measures of optimism are negatively related to growth in employment and revenues, after controlling for pre-entry experience.

However, the evidence relating the degree of optimism within entrepreneurs to experience also suggests that prior experience, particularly industry experience, reduces over-optimism. Landier and Thesmar, (2008), find that entrepreneurs with higher opportunity cost (measured as those with higher education levels) tend to be more optimistic about future performance (relative to actual), but industry experience reduces over-optimism. Fraser and Greene, (2006), find that experienced entrepreneurs are less over-optimistic. In our model, the impact of over-optimism on firm outcomes is similarly mixed, as shown in proposition 2 below.

An alternative formalization of this intuition could involve differences in entrepreneurial risk preferences. Entrepreneurs willing to take on riskier projects would plausibly have higher rates of failure but also cash-out rates. Without more detailed data, the risk based explanation

[5] Melmandier and Tate (2005) find that over-confident CEOs over-invest, thereby reducing the rate of return.

cannot be ruled out. More to the point, it is not necessary either. Our story is simply that higher opportunity cost entrepreneurs are impatient for success and willing to accept higher probability of failure in return. This may involve riskier strategies, and a loose interpretation of our model below is consistent with this idea.

Finally, the interactions between investors and entrepreneurs has attracted a great deal of attention in the literature. For instance, Thesmar and Landier (2008) show that that over-optimistic entrepreneurs are more likely to enter into short term debt contracts, which leaves potentially them more vulnerable to being failing in the short term. They do not observe failure and cannot directly test their theory. We ignore the difference between investors and the entrepreneur, although in the analysis, we separately control for VC financed firms. T

3 Model

We develop a simple model to guide the empirical analysis. Our intent is not to argue for the applicability of this highly stylized model but rather to use it to formalize the intuition that high opportunity cost entrepreneurs, unwilling to linger on, are likely to accept higher risk of failure in return for a quicker cash-out.

3.1 Setup

Let P, $0 \leq P \leq 1$, represent the quality of a venture. One can think of P as a summary measure of all factors that drive success, including the quality of the entrepreneur and of the idea itself. In any period, the firm will cash-out with probability mP. A cash-out bestows a payoff of J on the entrepreneur. Entrepreneurs can increase m by investing c(m) per period, where c(m) is increasing and convex in m. One can think of c(m) as the "burn rate" in a startup. It is a commonplace among practitioners that although a higher burn rate may be needed to get the firm ready for acquisition or IPO, it also of increases the risk of failure. For instance, trying to succeed quickly could results in errors in hiring, product development or market positioning, leading to failure.

Failure results in a payoff of zero. The probability of failure in any period is (1-*P*)*m*, so that increasing *m* also increases the chance of failure. All else constant, higher quality ventures have lower probability of failure and higher probability of cash-out. Moreover, the marginal increase in the probability of failure as *m* increases is lower for higher quality ventures. Conversely, the marginal payoff of *m* in increasing the probability of cash-out is higher for higher quality ventures.

The probability that an entrepreneurs neither succeeds or fails is 1-*mP*-(1-*P*)*m* or simply (1-*m*).The entrepreneur has an opportunity cost of α for every period the firm survives, and β (0≤ β≤1) is the discount factor.

Finally, we assume stationarity. Specifically, the probability of cash-out and failure are functions only of the current burn rate *m* and independent of past levels of *m.* It follows that future value of a firm, V, is the same in every period that the firm survives. It also follows that a firm will optimally choose the same *m* for each period it survives.

For analytical tractability, we assume that $c(m)\equiv m^2/2$. Thus the expected profits of an entrepreneur with an opportunity cost of α in period t is given by

$$V = Max_m \{mpJ + \beta V(1-m) - \frac{m^2}{2} - \alpha\} \qquad (1)$$

Let m^* denote value that maximizes (1). The first order condition for an interior optimum is

$$\frac{\partial V}{\partial m} = PJ - \beta V - m = 0 \qquad (2)$$

Rearranging terms in (1), we have

$$V = \frac{mpJ - \frac{m^2}{2} - \alpha}{1-\beta(1-m)} \qquad (3)$$

Solving for V using equations (2) through (3) gives us values for V.

$$V = \frac{(1-\beta(1-PJ) \pm \left[((1-\beta(1-PJ))^2 + 2\beta^2\left(\alpha - \frac{P^2J^2}{2}\right)\right]^{1/2}}{\beta^2} \quad (4)$$

In (4) above, only one feasible value of V guarantees that *m* is between 0 and 1. This is

$$V = \frac{(1-\beta(1-PJ) - A^{1/2}}{\beta^2} \quad (5)$$

where

$$A \equiv ((1-\beta(1-PJ))^2 + 2\beta^2\left(\alpha - \frac{P^2J^2}{2}\right) \quad (6)$$

The first order condition implies that the optimal burn rate, *m*, is

$$m^* = \left(1 - \frac{1}{\beta}\right) + \frac{A^{1/2}}{\beta}.^{6} \quad (7)$$

Note that A is increasing in α, and *m** is increasing in A, so that m^* is increasing in α.

Result 1: Entrepreneurs with higher opportunity costs have higher burn rates.

<u>Opportunity costs and hazard of cash-out and failure</u>

The hazard of cash-out – the probability that a firm cashes out in period t given that it survives till t – is $\Phi \equiv m^*P$. Because *m** increases with α, the hazard of a cash-out is also increasing in α.

Prediction 1: Entrepreneurs with higher opportunity costs have a higher hazard of cash-out.

The probability that a firm fails in period t, given it has survived till t, is $\Omega \equiv m^*(1-P)$, which is increasing in *m**, so that the hazard of failure increases with α as well.

Prediction 2: Entrepreneurs with higher opportunity costs have a higher hazard of failure.

<u>Quality of venture and hazard of cash-out</u>

[6] Note that since $0 \leq m \leq 1$, $A^{1/2}$ is bounded between 1-β and 1. Moreover since V>0, $\beta(PJ + \beta - 1) > A^{1/2}$.

The partial derivative of m^* with respect to P, the quality of the venture, is $J(1-\beta)A^{-1/2} > 0$, so that m^* increases in P. Intuitively, a higher P raises the marginal product of m by increasing the probability of cash-out and lowering the probability of failure.

Result 2: Higher quality ventures have higher investment rates, m.

This result implies that higher quality ventures are more likely to succeed. Since m^* is increasing in P, it follows that higher quality ventures, all else equal, are more likely to succeed.

Prediction 3: The hazard of cash-out is higher for higher quality ventures.

<u>Interactions between venture quality and opportunity cost</u>

Thus far, the predictions of the model have been straightforward. A less obvious prediction is about the interaction between venture quality and entrepreneurial opportunity cost. Formally, we show in the appendix that $\frac{\partial^2 \Phi}{\partial \alpha \partial P} > 0$. This implies that high opportunity cost entrepreneurs are more likely to succeed when they are in a better quality venture.

Prediction 4: The hazard of cash-out rises faster with entrepreneurial opportunity cost for a high quality venture than a low quality one.

The effect of venture quality on failure is, however, not clear-cut. An increase in P has two opposing effects. While a higher quality venture has a lower hazard of failure for a given rate of investment, higher quality increases m^*, which increases the hazard of failure. We show in the appendix that for low values of P, the hazard of failure in increasing in P because the latter effect dominates. For high values of P, the direct effect dominates.

Prediction 5: The average effect of venture quality on failure is ambiguous. For low values of venture quality, the hazard of failure increases with venture, while for high values of venture quality, the hazard of failure decreases with venture quality.

Although the average effects are ambiguous, we show in the appendix that $\frac{\partial^2 \Omega}{\partial \alpha \partial P} < 0$. Thus, the marginal effect of opportunity cost on failure is lower for higher quality ventures.

Prediction 6: The hazard of failure rises more slowly with opportunity costs for high quality ventures than for low quality ventures.

4 Data and measures

Our sample consists of 286 ISM startups, followed from the time of entry till 2004 or their exit (cash-out or failure), whichever is earlier. From the Corptech directory, we obtained names of all startups that entered ISM between 1989 and 2004. We augmented the dataset with hand collected information about the founders (for up to 4 founders) from a variety of publicly available data sources on the Internet such as ZoomInfo (www.zoominfo.com), LinkedIn (www.linkedIn.com), Google Archives (www.archives.google.com) Internet Archive (www.archive.org), EDGAR database and Zephyr databases. For firms with multiple founders, the founder with the highest work experience was designated as the main founder and his or her characteristics were then used to characterize the startup.

Failure: Firms in the sample exited either due to two reasons: the business was dissolved or acquisition by another firm. We defined a startup as having failed if it ceases to exist but was not acquired on favorable terms. Thus distress sales are treated as failures as are cases where the business is simply dissolved.[7] We identified the year of failure as the year in which the corporate

[7] We used two criteria to determine if an acquisition was a distress sale: (1) if the firm was sold for less than $1 million and (2) if the transaction was an asset purchase, determined from the press release of the acquisition. For instance, if the press release stated that the merger was an "asset purchase", we classified such mergers as a distress sale e.g. Netopia acquisition of DoBox Inc http://www.bizjournals.com/sanfrancisco/stories/2002/04/01/daily4.html (last accessed july 27, 2008), Contentwatch acquisition of NetNanny software see http://www.manac.com.au/releases/44/Net_Nanny.pdf (last accessed July 27th 2008). Acquisitions that failed both criteria were treated as a cash-out. A total, of 79 firms in our sample were acquired, of which 11 of the acquisitions were classified as being distress.

web site was last available on archive.org, a site that contains historical archives of all Internet web sites. The year of failures in the case of distress sale was year of the sale.

Cash-outs: We define cash-out as a favorable acquisition, or an Initial Public Offering (IPO), whichever was earlier. The date of acquisition was identified using the Zephyr database, a database that tracks all mergers and acquisitions from 1985.

Opportunity cost: To measure the opportunity costs of an entrepreneur, one would ideally need to measure the discounted present value of future earnings in the entrepreneur's next preferred alternative. This is infeasible. We develop two proxies for opportunity costs. Our main measure is the number of years of work experience (work experience, henceforth) of the most experienced founder among all the founders of the focal firm. We developed this measure by first calculating the number of elapsed years from the year of last graduation until the year of founding of the focal startup, for every identified founder of the startup. This measure assumes that greater work experience is associated with higher wage earnings. Bhide, (2000), for instance, argues that entrepreneurs in an "established corporate track" are unlikely to start a venture since they would have to give up a very lucrative job in order to startup a firm.

We also experimented with a second measure, namely the total number of organizations (previous jobs henceforth) that the main founder of the startup had worked for.[8] Note however that the two measures are highly correlated (corr – 0.64), and our results are very similar with the second measure as well.

Our measures of opportunity costs have obvious limitations. For instance the number of previous jobs may also capture preference of entrepreneurs to move on from one job to another.

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[8] We developed this measure using the following procedure: Using detailed founder histories in www.zoominfo.com and www.linkedin.com, we first counted the number of organizations or previous jobs that each founder of the startup worked in. We use the previous jobs of the founder that had the maximum number previous jobs held among all founders of the startup as our measure of opportunity cost. Since founders that have held many previous jobs are likely to have more alternatives they are also likely to have high opportunity costs of entrepreneurship.

Such entrepreneurs, contrary to our assumption, could actually have been earning lower wages and may also have lesser opportunity costs of entrepreneurship. Further this measure may not measure other non-pecuniary benefits to stay on as entrepreneurs (Hamilton, 2000; Moskowitz and Vissing-Jorgenson, 2002). Perhaps the most salient of the limitations is that both these measures could also pick up differences in the underlying venture quality, *P*. For instance, more experienced entrepreneurs may be more likely to enter with a better quality venture. In order separate out any such confounding effects we use initial scale as a measure of venture quality.

Venture quality: We use the initial size at entry, (initial scale) measured as the number of employees at the time of entry. The literature has argued that initial size of firms is a good proxy for the quality of startups (Mata and Portugal, 1994; Agarwal and Audretsch, 2001).[9] In our main analysis, we exclude 35 firms that do not report their initial size. However as a robustness check we include these firms by assigning the minimum value of initial size (2 employees) to firms that do not report their initial size.

Internet Bust years: This variable is =1 if the focal firm was founded after 2000, on the grounds that 2000 was the year the Internet bubble burst. Arguably a greater fraction of such firms were started by entrepreneurs that were unemployed after the bubble burst. These entrepreneurs would have lower opportunity cost. Accordingly, we use this variable both as a control for the entry cohort, and also as a robustness check of our theory.

Marketing Capability: We measure the marketing capability of startups using the number of IT trademarks that the parent of the startup owned (*parent trademarks*, henceforth), at the time of

[9] These include 25 firms for which the founders could not be traced and 10 other firms for which the founders were traced but did not report initial scale. For 4 firms that reported initial scale, we could not trace the founders.

entry.[10] In cases where the startup had multiple parents, we use the number of IT trademarks of the parent with the greatest number of IT trademarks.

Technical capability: We use the number of U.S. information security patents of the founders, as well as any patents assigned to the startup when it was formed. Information security patents are those in the US patent technological classes 705 subclass 50-79, 380 and 726. As is standard in the literature, we weight each patent by forward citations, adjusting for year of grant.

Market Segment Fixed Effects: We distinguish 8 market segments: encryption products, network security, authentication, firewalls, antivirus, spam control, hardware, and consulting. [11] Accordingly, we use both market 7 segment fixed effects, with consulting being the residual category. The first four segments use encryption technology as an input. As discussed later, we allow for unobserved heterogeneity, whose distribution is also allowed differ between firms that use encryption technology as an input and firms that do not.

Firm age: This variable is measured as the number of calendar years from the year of entry until the year of failure, cash-out or 2004, whichever is earlier. We use this measure to control for age dependence (Dunne, Roberts, and Samuelson, 1988; Evans, 1987; Audretsch and Mahmood, 1995Mata and Portugal,1994;). To allow for non-linearities, we also include the square term.

Industry age: It is plausible that firm survival may vary as the industry grows and matures (e.g., Agarwal and Gort, 2002). We control for this using Industry age, which is simply the number of years from 1970.

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[10]We collected this variable by using a keyword search on the US PTO trademarks database (http://tess.uspto.gov). We used the following search query on the trademark database. Trademark description includes ("computer") OR ("hardware") OR ("pixel") OR ("telecom") OR ("telecommunications") OR ("software") OR ("Wireless") OR ("computing") OR ("database") OR ("data base ") OR ("pixels") OR ("computer program") OR ("Network") OR ("LAN") OR ("Networking") OR (" computer protocol ") OR (" Internet ").

[11] Note that we only measure the segment of entry.

<u>Entrant type:</u> We classified startups into one or more of the following categories based on the immediate prior experience of founders: *related startups* (founded by employees of computer hardware, software, IT consultancies, or telecommunication firms or ISM firms), *unrelated startups* (founders from defense, finance, aerospace and automobile industries), *serial* startups (startups founded by serial founders) and *other* startups, with founders from universities or hackers, or startups whose sources could not be traced.[12]

<u>Source of capital dummies:</u> In many of our specifications we also control for the source of capital of startups. We distinguish between three funding sources – venture capital (VC dummy), corporate venture capital (CVC dummy), and others, presumably self-funded. The funding is measured at the time of entry and is self-reported.

Table 1 Description of measures used

Variable	Description	Source of variation	N	Mean	Std. Dev
Failure	=1 if the startup went into a distress sale or went out of business completely.	Firm	286	0.23	
Cash-out	=1 if the startup was acquired on favorable terms or had an IPO	Firm	286	0.20	
Work experience	Log (1+ # years of work experience) of the main founder. This is one of our proxies for opportunity cost	Firm	279[a]	1.27	1.63
Log (initial scale)	# employees of the startup at the time of entry. This is our proxy for the quality of the opportunity.	Firm	251[c]	3.23	1.58
Log (1+security patents)	Log of 1+ # of forward citations weighted security patents held by a firm at entry. This variable proxies technical capability	Firm	286	0.32	0.74
Log(1+ parent IT trademarks)	# trademarks held by the most prominent parent of the startup at entry.	Firm	286	1.07	1.89
Industry age	Age of the industry measured from 1970		286	8.87	5.68
Firm age	Calculated as current year – ISM entry year		286	6.88	4.94
Internet bust years	Dummy variable that indicates if the startup entered in post internet bubble era.		286	0.45	-

[a] Founder histories for a total of 29 startups could not be traced. Of these 4 report initial scale.

[c] A total of 35 startups do not report their initial size out of which, 25 were those for which the founders also were not traceable.

[12] A hacker was defined as a founder who was unemployed immediately prior to founding.

<u>Founding team education and experience controls:</u> We also use four education dummies (a degree in computer science or electrical engineering, and for non CS and non EE, whether there is a PhD, a masters, or a bachelors), and 3 prior experience dummies (if founder has engineering, sales, or top management experience).

Table 1 summarizes the measures and provides descriptive statistics. Around a quarter of the startups in our sample fail, and about a fifth succeeded in cashing-out. Slightly more than half were still in existence at the time of analysis. Slightly less than half of the firms were founded after 2000, and over a third of them received venture capital funding.

5 Empirical analysis

Table 2- Sources of entry in ISM

Entrant type	ISM	Mean work exp.(yrs)
Others	18%	2.69
		(1.05)
Related startups	52%	12.70
		(0.98)
Unrelated Startups	26%	4.52
		(1.25)
Serial entrepreneur	7%	7.91
		(2.52)

<u>Notes:</u> The total proportion adds up to more than 100% because many firms have multiple founders
Related: Founder worked in ICT (hardware, software, Internet, telecom) sector
Unrelated: Founder worked in non-ICT sector.
Serial: Founder has done a startup earlier.
Others: Includes hackers, or founders with no experience and university founders

As table 2 shows, entrants into the ISM were of diverse origins, with a fair degree of variation in prior work experience. Table 3 provides the share of cash-outs and failures, by entrepreneurial opportunity cost and venture quality. Comparing columns (b) and (c) shows that, as predicted, higher entrepreneurial opportunity cost increases the cash-out share (0.28 compared to 0.19) as well as share of failure (0.30 compared to 0.19). The differences in both cases are statistically significant. As predicted, higher venture quality increases the cash-out share from 0.12 to 0.33 (column a). The model did not have a clear prediction about how venture quality affects failure. Column (d) shows that venture quality decreases share of failure. This suggests that our measure of venture quality, namely initial scale, is plausibly a good summary measure of the overall quality of the venture, which includes both the quality of the idea, as well as the quality of the founding team.

Our model also had two other predictions. The first was that the share of cash-out would increase with opportunity cost faster for higher quality ventures. In column (b-c) comparing row (1) with row (2), we see that for high quality ventures the difference in cash-out probabilities is 0.16, whereas the difference is 0.05 for low quality ventures. Albeit statistically insignificant, the “difference-in-difference” is 0.11. The second prediction was that the share of failure should increase with opportunity cost more slowly for higher quality ventures. Once again comparing rows (1) and (2), column (e-f) shows that the difference in failure share is 0.06 for high quality ventures, whereas it is 0.14 for low quality, with the difference-in-difference being –0.08. Once again note that this estimate is not statistically significant.

Table 3: Share of cash-out and failure, by entrepreneurial opportunity cost and venture quality.

	Share of cash-out				Share of failure			
	Overall (a)	High opp. cost (b)	Low opp. cost (c)	(b-c)	Overall (d)	High opp. cost (e)	Low opp. cost (f)	e-f
High Quality (1)	0.33	0.41	0.25	0.16	0.17	0.19	0.13	0.06
	(0.04)	(0.06)	(0.05)	(0.08)	(0.03)	(0.05)	(0.04)	(0.06)
Low Quality(2)	0.12	0.16	0.11	0.05	0.33	0.39	0.25	0.14
	(0.03)	(0.05)	(0.04)	(0.07)	(0.04)	(0.07)	(0.05)	(0.09)
(1)- (2)	0.21	0.25	0.14	0.11	-0.16	-0.20	-0.12	-0.08
	(0.05)	(0.08)	(0.07)	(0.10)	(0.05)	(0.09)	(0.07)	(0.11)
Overall		0.28	0.19	0.09		0.30	0.19	0.11
		(0.04)	(0.03)	(0.05)		(0.04)	(0.03)	(0.05)

<u>Notes</u>:
High Quality: Startups with initial scale above the average
Low Quality: Startup with initial scale below average.
High Opp. Cost: Startups with entrepreneurial work experience above average.
Low Opp. Cost: Startups with entrepreneurial work experience above average.
The standard errors are provided in parentheses.

Note that this table shows shares, rather than the per-period probabilities, and thus, does not control for the differences in when different types of firms entered the industry. Further, this table does not take into account that cash-outs and failures are mutually exclusive, and thus, not independent outcomes. These issues are addressed by estimating a discrete time hazard regressions that jointly estimates the hazard of failure and cash-outs. The results of this simple cross-tabulation are nonetheless significant in that all the major predictions of our simple model are borne out here, including the far from obvious predictions on the signs of the cross-partials.

We now turn to discrete time hazard analysis. In the context of our data there are two absorbing states that a startup can transition into, which are failure and cash-out or cash-outs. Following Boyd *et al.*, 2005 we implement a discrete time hazard regressions specification that is widely used in the literature (Martin and Mitchell, 1998King and Tucci, 2002;).[13]

In our model, a firm *i* that is alive in a given year has a probability of cash-out given by $P_i m_i$, of failure given by $(1-P_i)m_i$, and of survival to the next period of $(1- m_i)$. This leads to a straightforward nested specification, in which survival is decided first with probability $(1- m_i)$, and conditional upon survival, the share of cash-out and failures is $P_i/(1-P_i)$. However, the nested specification depends critically on the assumption that an increase in venture quality affects cash-out and failure in strict proportionality to *m*. A more general specification would allow the probability of cash-out to be $P_i m_i + u_{ic}$, and similarly, the probability of failure to be $(1-P_i)m_i + u_{if}$. This more general specification suggests a multinomial logit with unobserved heterogeneity. Thus, in our baseline specification, the probability of cash-out for the i^{th} firm is $\frac{\exp(X_i\beta_c+u_{ic})}{1+\exp(X_i\beta_c+u_{ic})+\exp(X_i\beta_f+u_{if})}$ where X_i represents the observed characteristics of the entrepreneur and venture, such as experience, startup size and market segment, and u_{ic} and u_{if} represent firm

[13] Continuous time specifications yield qualitatively similar results. For instance Cox proportional hazard specifications that estimates the hazard of exit and cash-outs separately, yield qualitatively similar results.

specific unobserved heterogeneity. The probability of failure and survival are analogously specified. We follow Heckman and Singer, (1984) and Boyd et al., (2005) and assume that the unobserved heterogeneity can be represented by a discrete distribution that we estimate non-parametrically. We allow for the distribution to differ between the firms that use encryption technology and firms that do not. Specifically, we assume that $u_{ic} = a_{0ic}+a_{1ic}$*encryption, where encryption = 1 if the startup enters encryption products, network security, or authentication markets, and = 0 otherwise, and similarly for the u_{if}.[14] Ignoring unobserved heterogeneity altogether does not significantly alter our results.

Table 4A –Competing hazard regressions of failure or cash-out[a]

	Spec. 1		Spec. 2	
	Failure	Cash-out	Failure	Cash-out
Log(1+ work exp.)	0.29 ***	0.26 **	0.28 ***	0.25 *
	(0.02)	(0.13)	(0.03)	(0.15)
Log (initial size)	-0.22 ***	0.40 ***	-0.24 ***	0.34 ***
	(0.03)	(0.04)	(0.04)	(0.03)
Log (1+ patents)	-0.05	0.23 *	-0.06	0.19 *
	(0.04)	(0.16)	(0.04)	(0.12)
Log(1+parents IT TM)	-0.20 ***	0.17	-0.21 ***	0.14
	(0.05)	(0.11)	(0.05)	(0.09)
Related startup	0.54 *	0.82 ***	0.57 *	0.76 ***
	(0.23)	(0.21)	(0.25)	(0.19)
Unrelated startup	-0.26 ***	0.11	-0.28 **	0.15
	(0.07)	(0.50)	(0.12)	(0.22)
Serial entrep.	0.64 ***	1.13 ***	0.61 ***	1.08 ***
	(0.18)	(0.30)	(0.18)	(0.35)
Firm age	-0.04 *	0.11 *	-0.05 *	0.12
	(0.02)	(0.07)	(0.02)	(0.06)
Firm age^2	0.00 ***	0 **	0.01	-0.01
	(0.00)	(0.00)	(0.01)	(0.00)
Industry age	-0.27 *	-0.25 *	-0.29 ***	0.28
	(0.15)	(0.16)	(0.13)	(0.21)

[14] We get qualitatively similar results even if we do not include an encryption dummy.

Table 4A (cont) –Competing hazard regressions of failure or cash-out[a]

	Spec. 1				Spec. 2			
	Failure		Cash-out		Failure		Cash-out	
Industry age^2	-0.04	***	0.03	***	-0.03	***	0.03	***
	(0.00)		(0.00)		(0.00)		(0.00)	
VC dummy					0.23	***	0.85	**
					(0.07)		(0.38)	
CVC dummy					0.13		0.24	
					(0.08)		(0.08)	
Internet bust years	-1.12	***	-0.86	***	-1.11	***	-0.82	***
	(0.20)		(0.23)		(0.20)		(0.19)	
Constant	-2.78	***	-5.24	***	-2.7	***	-5.07	***
	(0.10)		(0.90)		(0.13)		(1.04)	
LL	-393.09				-391.07			
Location parameter 1	-1.44, 1.75				-1.32, 1.29			
Location parameter 2	-0.11, 0.13				-0.51, 0.19			
Variance	2.52, 0.01				1.72, 0.10			
Covariance	0.19				0.26			
Probabilities	0.55, 0.45				0.51, 0.49			

Notes: ***Significant at 1%. ** Significant at 5%. * Significant at 10%. [a]Standard errors in parentheses cluster corrected by firm. The unit of observation is firm, year. [b]For 4 firms that report initial scale, we cannot trace founders and 35 firms do not report initial scale. All specifications include 7 submarket dummies, 4 founder education dummies, and 3 founder work history dummies. The number of observations is 1998 for 247 firms.

We use 1998 observations, consisting of an observation per firm year from the year of entry till year of failure, cash-out or 2004 whichever is earlier. In our baseline specification, we exclude observations relating to 39[15] firms since data on initial scale or, less frequently, on founder characteristics, was missing. Including the dropped observations by including a dummy variable indicating the missing measure for both initial size as well as experience leaves our results unchanged.

The results are shown under specifications 1 and 2 of table 4A and specifications 1 and 2 of table 4B. That the results of the specification 2 of table 4A, which includes VC and CVC dummies, are qualitatively similar to those that exclude these dummies, suggests that any

[15] As noted earlier this comprises of 25 firms that did not reported initial size and were started up by founders that could not be traced; 10 firms that did not report their initial size but for which we could acquire data on prior experience; and 4 firms that reported initial size but for which prior work experience could not be traced.

endogeneity on account of including these dummies, if any does not significantly bias the coefficients of interest. It also indicates that our results on the effects of opportunity cost are not driven by differences in funding sources. In particular, these results do not merely reflect the plausible association between entrepreneurial experience and VC funding, and the desire of VCs for quick exits. Specification 1 of table 4B, which includes the dropped observations with a dummy variable that controls for the missing measures (no size dummy for firms that do not report initial size and experience not found dummy for firms whose founders were not traceable) yields results very similar to those in table 4A. Note that our results are consistent across these specifications and in particular results of table 4B shows that dropping 39 firms does not influence our principal results shown in specification 1 of table 4A.

As in table 3, the results of specification 1 of table 4A, indicate that entrepreneurs with higher opportunity costs are more likely to fail. For instance, from specification 1, a one standard deviation increase in experience is increases the hazard of failure by about 21%. Initial scale, however, reduces failure – the estimated coefficient is negative and statistically significant. Results of the cash-out equation imply that entrepreneurs with higher opportunity costs are more likely to cash-out as well: In specification 1, a standard deviation increase in work experience is associated with about a 19% in the hazard. The coefficient of initial scale is positive and significant suggesting that high quality ventures are more likely to succeed. The different effects of initial scale on cash-out and failure, in contrast to the effects of entrepreneurial work experience, are noteworthy. It suggests that our results are not driven by unobserved measures of quality and that our attempts to control for enterprise quality by measuring initial scale and allowing for unobserved differences across firms have not been in vain.

As further evidence, note that the coefficient for firms founded after 2000, the Internet bust years, is negative and significant in both the cash-out and failure equation. After 2000, the drying up of the IPO market would likely reduce cash-outs. However, it should also have increased failure (rather than decreased it). The lower rates of failure are consistent with improved venture quality as many low quality ventures that might have been launched earlier were not started. However, increased quality ought to have resulted in higher cash-out rates. The lower rates of failure and cash-outs are, however, consistent with the hypothesis that entrepreneurs in IT sectors had fewer outside options after the Internet bubble ended. Thus, this represents an additional test of our theory that entrepreneurial opportunity cost raises both cash-outs and failures.

In specification 1 of table 4B we also include startups that did not report their initial size by assigning the minimum value of initial size (1.09) to startups that did not report their initial size along with a dummy variable, size not reported=1, if the focal startup did not report initial size. In addition we also include startup, for which none of the founders were traceable by assigning zero to prior experience of the founder of such startups along with including prior experience not traced dummy=1 for startups for which the founders could not be traced. Dropping the observation with missing data does not appear to affect our results.

Table 4B –Competing hazard regressions of failure or cash-out, no dropped observations [a]

	Failure	Cash-out
Log(1+ work exp.)	0.18 ***	0.33 ***
	(0.03)	(0.10)
Founder not traced	0.13	-2.11 ***
	(0.14)	(0.13)
Log (initial size)	-0.21 ***	0.36 ***
	(0.03)	(0.11)
Size not reported	0.03	-0.58
	(0.18)	(0.61)

Table 4B (cont.) –Competing hazard regressions of failure or cash-out, no dropped observations [a]

	Failure	Cash-out
Log (1+ patents)	-0.09	0.22 *
	(0.08)	(0.12)
Related startup	0.55 ***	0.46 ***
	(0.12)	(0.15)
Unrelated startup	-0.26	0.13
	(0.29)	(0.13)
Serial entrep.	-0.58 ***	0.81 ***
	(0.08)	(0.16)
Firm age	-0.03 *	0.10
	(0.01)	(0.06)
Firm age^2	0.00	0.00
	(0.00)	(0.00)
Industry age	-0.25 *	-0.24 *
	(0.15)	(0.15)
Industry age^2	-0.04 ***	0.03 ***
	(0.01)	(0.00)
Internet bust years	-1.23 ***	-0.68 ***
	(0.10)	(0.16)
Constant	-2.52 ***	-4.76
	(0.09)	(0.43)
N	2809	
No. of firms	286	
LL	-386.23	
Location parameter 1	-1.22, 1.80	
Location parameter 2	-0.18, 0.48	
Variance	2.79, 0.01	
Covariance	0.28	
Probabilities	0.52, 0.48	

Notes: ***Significant at 1%. ** Significant at 5%. * Significant at 10%. [a]Standard errors in parentheses cluster corrected by firm. The unit of observation is firm, year. [b] For 4 firms, that report initial scale, we cannot trace founders and 35 firms do not report initial scale. All specifications include 7 submarket dummies, 4 founder education dummies, and 3 founder work history dummies.

In the final set of regressions, we test predictions that cash-outs should increase more rapidly with opportunity cost for high quality ventures, but failures should increase more slowly. We estimate separately for firms with above and below average initial scale. From table 5, when the initial entry scale is low, a one standard deviation increase in work experience increases the hazard of failure by 24%, whereas the same change increases failure by only 3% for high quality ventures. The difference between “high” and “low” is -0.21, (standard error 0.12[16]; p-value 0.08).[17] A one standard deviation increase in work experience increases cash-out hazard 7% for low quality ventures, and 128% for high quality ventures. The differences is both large and statistically significant (p-value = 0.00).

[16] Boot strapped standard error from 20 iterations.
[17]The standard errors are obtained by bootstrapping, based on 20 iterations..

Table 5 –Competing hazard regressions of failure or cash-out by high and low quality[a]

	Low Quality		High Quality	
	Failure	Cash-out	Failure	Cash-out
Log(1+ work exp.)	0.32 ***	0.11	0.05 **	0.72 ***
	(0.07)	(0.07)	(0.02)	(0.10)
Log (1+ patents)	-0.11 ***	0.10	-0.03	0.19 *
	(0.03)	(0.06)	(0.11)	(0.12)
Log(1+parents IT TM)	-0.28 ***	0.15	-0.27 ***	0.14
	(0.12)	(0.17)	(0.11)	(0.09)
Related startups dummy	0.73 ***	0.80 ***	0.21	0.76 ***
	(0.04)	(0.01)	(0.21)	(0.19)
Unrelated startups dummy	-0.39 ***	-0.09	-0.44 ***	0.15
	(0.09)	(0.10)	(0.04)	(0.22)
Serial entrep. Dummy	0.11	0.78 ***	0.46	1.08 ***
	(0.17)	(0.20)	(0.88)	(0.35)
Firm age	-0.03	0.09	-0.06 **	0.12
	(0.02)	(0.06)	(0.02)	(0.06)
Firm age^2	-0.00 **	-0.00 **	0.01	-0.01
	(0.00)	(0.00)	(0.01)	(0.00)
Industry age	-0.17 *	-0.31 ***	-0.24 **	0.28
	(0.08)	(0.12)	(0.13)	(0.21)
Industry age^2	-0.04 ***	0.03 ***	-0.01	0.03 ***
	(0.00)	(0.00)	(0.00)	(0.00)
Internet bust years	-0.60 ***	-0.88 ***	-1.59 ***	-0.82 ***
	(0.15)	(0.02)	(0.35)	(0.19)
Constant	-8.19 **	-8.04 ***	-4.44 *	-5.07 ***
	(3.20)	(0.60)	(2.40)	(1.04)
N	1076		922	
No. of firms	132[b]		115	
LL	-154.17		-148.91	
Location parameter 1	-1.01, 2.75		-1.46, 1.15	
Location parameter 2	-1.24, 0.03		-0.78, 0.06	
Variance	2.12, 0.03		1.41, 0.19	
Covariance	0.22		0.29	
Probabilities	0.52, 0.48		0.54, 0.46	
Submarket dummies	7		6	

Notes: ***Significant at 1%. ** Significant at 5%. * Significant at 10%. [a]Standard errors in parentheses cluster corrected by firm. The unit of observation is firm, year. [b] For 4 firms, that report initial scale, we cannot trace founders and 35 firms do not report initial scale. All specifications 4 founder education dummies, and 3 founder work history dummies. High quality = initial scale above average. Low quality = initial scale below average.

Robustness checks

A. **Alternative measure of opportunity cost**.

We replicated our results using the number of previous organizations the entrepreneur had worked in, as a measure of opportunity cost (results shown below in tables 6A and 6B). Since founders that have held many previous jobs are likely to have more alternatives they are also likely to have high opportunity costs of entrepreneurship. However, it may also capture the preference of entrepreneurs to move on from one job to another. Such entrepreneurs, contrary to our assumption, could actually have been earning lower wages and may also have lower opportunity costs of entrepreneurship. However, this measure is highly correlated with work experience (coefficient of correlation = 0.64). Not surprisingly, we find that our principal findings are unchanged (results shown in tables 6A and 6B).

Table 6A –Competing hazard regressions of failure or cash-out, number of jobs as alternative measure of opportunity cost[a]

	Failure	Cash-out
Log(1+ prev. jobs.)	0.27 ***	0.32 **
	(0.05)	(0.15)
Log (1+ patents)	-0.12	0.21 **
	(0.12)	(0.10)
Log(1+parents TM)	-0.13 ***	0.16 *
	(0.04)	(0.08)
Log (init. scale)	-0.21 ***	0.44 ***
	(0.02)	(0.11)
Related startups dummy	0.50 ***	0.85 ***
	(0.20)	(0.29)
Unrelated startups dummy	-0.22 **	0.06
	(0.12)	(0.32)
Serial dummy	0.63 ***	0.81 ***
	(0.11)	(0.13)
Internet bust years	-1.18 ***	-0.81 ***
	(0.15)	(0.22)
Firm age	-0.13 ***	0.20 ***
	(0.01)	(0.07)
Firm age^2	0.00 ***	-0.00 *
	(0.00)	(0.00)
Industry age	-0.24 *	-0.20
	(0.10)	(0.15)

Table 6A (cont.) –Competing hazard regressions of failure or cash-out, number of jobs as alternative measure of opportunity cost[a]

	Failure	Cash-out
Industry age²	-0.03 ***	0.01
	(0.00)	(0.00)
Constant	-2.94 ***	-5.46 ***
	(0.15)	(0.96)
N	1998	
No. of firms	247[b]	
LL	-391.33	
Location parameter 1	-0.26, -0.10	
Location parameter 2	-0.07, 0.27	
Variance	0.51, 0.17	
Covariance	-0.30	
Probabilities	0.22, 0.78	

Notes: ***Significant at 1%. ** Significant at 5%. * Significant at 10%. [a] Standard errors in parentheses cluster corrected by firm. The unit of observation is firm, year. [b] For 4 firms, that report initial scale, we cannot trace founders. All specifications include 7 submarket dummies, 4 founder education dummies, and 3 founder work history dummies.

Table 6B –Competing hazard regressions of failure or cash-out by high and low quality, using number of jobs as alternative measure of opportunity cost[a]

	"Low" quality		"High" quality	
	Failure	Cash-out	Failure	Cash-out
Log(1+ prev. jobs.)	0.67 ***	0.20 ***	0.17 ***	0.51 ***
	(0.16)	(0.08)	(0.06)	(0.14)
Log (1+ patents)	-0.12 ***	0.06	-0.12	0.15 **
	(0.05)	(0.08)	(0.26)	(0.08)
Log(1+parents IT TM)	-0.38 ***	0.25	-0.29 ***	0.14 *
	(0.17)	(0.18)	(0.14)	(0.08)
Related startups dummy	0.84 ***	0.61 ***	0.20	0.61 ***
	(0.09)	(0.07)	(0.22)	(0.16)
Unrelated startups dummy	-0.14 ***	-0.06	-0.39 ***	0.06
	(0.06)	(0.14)	(0.05)	(0.14)
Serial entrep. dummy	0.54	0.84 ***	0.66	0.85 *
	(0.68)	(0.25)	(1.12)	(0.45)
Firm age	-0.01	0.06 *	-0.05 **	0.08 *
	(0.02)	(0.03)	(0.02)	(0.05)
Firm age^2	-0.00 *	-0.00 *	0.01	-0.01
	(0.00)	(0.00)	(0.01)	(0.00)
Industry age	-0.18 *	-0.50 **	-0.23 *	0.29
	(0.10)	(0.29)	(0.16)	(0.22)
Industry age^2	-0.03 **	0.03 **	-0.01	0.02 ***
	(0.00)	(0.01)	(0.00)	(0.00)
Internet bust years	0.90 ***	-0.83 ***	-1.29 ***	-0.82 ***
	(0.16)	(0.17)	(0.23)	(0.19)
Constant	-7.90 **	-7.95 ***	-4.46 ***	-3.06 ***
	(0.04)	(0.29)	(1.37)	(0.78)
N	1076		922	
No. of firms	132[b]		115	
LL	-166.31		-158.22	
Location parameter 1	-1.15, 2.36		-1.55, 1.12	
Location parameter 2	-1.34, 0.08		-0.88, 0.13	
Variance	2.64, 0.02		1.54, 0.18	
Covariance	0.29		0.28	
Probabilities	0.56, 0.44		0.55, 0.45	

Notes: ***Significant at 1%. ** Significant at 5%. * Significant at 10%. [a]Standard errors in parentheses cluster corrected by firm. The unit of observation is firm, year. [b] For 4 firms, that report initial scale, we cannot trace founders and 35 firms do not report initial scale. All specifications include 7 submarket dummies, 4 founder education dummies, and 3 founder work history dummies.

B. Results excluding VC funded firms:

Although we control the source of financing, VC funding firms may differ qualitatively from others. Accordingly, we replicate our results that relate to cash-outs and failures using a sample of 188 non-VC funded firms. The results shown in table 7 are similar to those in table

4A. Once again, entrepreneurs with high opportunity costs not only have higher failure hazards but have higher cash-out rates as well. A standard deviation increase in work experience is increases failure by about 18%, and cash-outs by 12%. Further, venture quality decreases failure and increases cash-outs.

Table 7 –Competing hazard regressions of failure or cash-out, non-VC funded firms only [a]

	Failure	Cash-out
Log(1+ work exp.)	0.25 ***	0.18 ***
	(0.04)	(0.06)
Log (1+ patents)	-0.09 **	0.14 **
	(0.11)	(0.06)
Log(1+parents TM)	-0.27 ***	0.18 *
	(0.12)	(0.10)
Log (init. scale)	-0.17 ***	0.42 ***
	(0.04)	(0.05)
Related startups dummy	0.56 ***	0.31 ***
	(0.32)	(0.13)
Unrelated startups dummy	-0.08	-0.17
	(0.20)	(0.32)
Serial dummy	0.64 ***	1.05 ***
	(0.12)	(0.42)
ISM tenure	-0.03 *	0.09
	(0.02)	(0.06)
ISM tenure^2	0.01	-0.01 *
	(0.01)	(0.00)
Internet bust years	-1.26 ***	-1.19 ***
	(0.23)	(0.29)
Industry age	-0.25 *	-0.25 **
	(0.15)	(0.12)
Industry age^2	-0.03 ***	0.01 **
	(0.00)	(0.00)
Constant	-2.63 ***	-5.36 ***
	(0.15)	(1.10)
N	1087	
No. of firms	151	
LL	260.41	
Location parameter 1	-0.02, 0.08	
Location parameter 2	-0.11, 0.27	
Variance	0.23, 0.62	
Covariance	0.35	
Probabilities	0.31, 0.60	

Notes: ***Significant at 1%. ** Significant at 5%. * Significant at 10%. [a] Standard errors in parentheses, cluster corrected by firm. The unit of observation is firm, year. All specifications include 7 submarket dummies, 4 founder education dummies, and 3 founder work history dummies.

C. Nested multinomial logit

Our model implies a nested structure for the stochastic outcomes, with the first level being survival or not, and conditional on survival, cash-out or success. As a robustness check, we estimate a simple multinomial logit. The qualitative results, shown in table 8, are similar to those reported above.

Table 8 –Nested logit specification, competing hazard of cash-out and failure [a]

	Failure	Cash-out
Log(1+ work exp.)	0.19 ***	0.18 ***
	(0.03)	(0.03)
Log (initial size)	-0.18 ***	0.29 ***
	(0.06)	(0.06)
Log (1+ patents)	-0.10	0.22 ***
	(0.08)	(0.07)
Log(1+parents IT TM)	-0.19 ***	0.06
	(0.05)	(0.06)
Related startup	0.32 *	0.24 ***
	(0.10)	(0.10)
Unrelated startup	0.01	0.03
	(0.08)	(0.13)
Serial entrep.	-0.38	0.59 ***
	(0.16)	(0.21)
Firm age	-0.03	0.24 ***
	(0.02)	(0.03)
Firm age^2	0.00 *	0.01 **
	(0.00)	(0.00)
Industry age	-0.15 ***	-0.23
	(0.04)	(0.19)
Industry age^2	-0.00	-0.01 *
	(0.00)	(0.00)
Internet bust years	-1.90 ***	-2.86 ***
	(0.46)	(0.29)
Constant	-3.52 ***	-3.80 ***
	(0.26)	(1.40)
LL	-354.35	

Notes: *** Significant at 1%. ** Significant at 5%. * Significant at 10%. [a] Standard errors cluster corrected by firm. The unit of observation is firm, year. [b] For 4 firms, that report initial scale, we cannot trace founders and 35 firms do not report initial scale. [c] 247 firms, 5994 obs. in all.[d] The first level nest is between survival and non survival. The second level is conditional on non survival, and the alternatives are cash-out or failure. chi2(1) for IIA - 1.43;p-value 0.23, inclusive value is 0.11 (0.5). All specifications include 7 submarket dummies, 4 founder education dummies, and 3 founder work history dummies.

6 Discussion

Our paper is motivated by a key characteristic of entrepreneurship common in technology intensive industries, namely that entrepreneurial ventures are started with the expectation that they have a high "upside" potential. The objective in founding a firm is often to have a sizable initial public offering or be acquired by an established firm, so as to yield a significant financial payoff to the entrepreneur (and other investors in the venture). Not all high-tech ventures share this characteristic, and conversely, startups in other industries (Starbucks comes to mind) may also be founded with the objective of being operated on a large scale. The operative point being that survival of the startup is not the objective.

It follow that the use of survival as a measure of performance, common in research in this area, is problematic. The problematic nature of survival as a measure of performance is well known to scholars. What is less well understood is that variations in survival may be systematically related to entrepreneurial characteristics in ways that obscure the relationship between entrepreneurial characteristics, strategy, and performance. Entrepreneurial opportunity cost is a case in point. Whereas they raise the threshold for staying on, in our paper, they also change the strategies of entrepreneurs. When the objective is to cash-out, we develop a simple model in which striving for a cash-out is not just directly costly, but also raises the probability of failure. High opportunity cost entrepreneurs put less value on surviving to try again, and hence, care less about failure. We find that high opportunity cost entrepreneurs will invest more aggressively, thereby increasing the chances of both cash-outs as well as failures. Although our model is couched in terms of burn rates, the intuition is broader. Higher opportunity cost entrepreneurs are in effect more impatient for success and willing to accept greater risks of failure in return.

Our model can be extended to deal with other types of differences across entrepreneurs as well. For instance, differences in time preference will yield similar results. All else held constant, entrepreneurs who discount the future more heavily, perhaps because they are older, will appear more impatient for success and more willing to tolerate failure. Similarly, although we do not have measures of the degree of confidence or optimism for entrepreneurs, and thus do not pursue this further, our model suggests that over-confident entrepreneurs will be willing to accept greater risk of failure in return for greater chances of success.

Our empirical results show that opportunity costs of entrepreneurship influences both success and failures. Entrepreneurs with high opportunity cost of entrepreneurship are both more likely to fail and more likely to succeed. Further, as predicted by our model, the impact of opportunity cost is conditioned by the overall quality of the venture. For higher quality ventures, the chances of success climb faster with opportunity cost than with lower quality ventures. But the reverse is true for failure. The chances of failure rise less rapidly with opportunity cost for higher quality ventures than for lower quality ventures.

As we have noted earlier, our model is simple. It cannot do justice to the rich set of strategies that entrepreneurs have. For instance, it ignores the interactions with investors, and how their objectives are reflected in the startup's strategies and objectives. Similarly our data are from a single industry in the IT sector. Thus, we cannot claim generality. Instead, our contribution is to show that understanding the implications of differences in entrepreneurial opportunity cost is but one step in understanding the implications of differences in entrepreneurial objectives for firm strategy and performance.

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Proof of propositions:

1. We first show that the derivation of V. Recall that we have two equations.

   $\frac{\partial V}{\partial m} = PJ - V - m = 0$ and $V = \frac{mpJ - \frac{m^2}{2} - \alpha}{1-\beta(1-m)}$. Substituting for V in the first order condition, we have $\frac{V^2\beta^2}{2} - \left(1-\beta(1-PJ)\right)V - \left(\alpha - \frac{P^2J^2}{2}\right) = 0$

   The only feasible solution $V = \frac{(1-\beta(1-PJ)) - A^{1/2}}{\beta^2}$ where $A \equiv \left(1-\beta(1-PJ)\right)^2 + 2\beta^2\left(\alpha - \frac{P^2J^2}{2}\right)$

   Using this value of V, $m^* = \left(1-\frac{1}{\beta}\right) + \frac{A^{\frac{1}{2}}}{\beta}$

2. We now show the conditions for $0 \le m^* \le 1$.

   $m^*>0$ implies $\left(1-\frac{1}{\beta}\right) + \frac{A^{\frac{1}{2}}}{\beta} > 0 \text{ } or \text{ } A > (1-\beta)^2$ and

   $m^* \le 1$ implies $\left(1-\frac{1}{\beta}\right) + \frac{A^{\frac{1}{2}}}{\beta} \le 1 \text{ } or \text{ } A \le 1$

3. We now show the condition that ensures V>0.

   If V>0, we need $\left(1-\beta(1-PJ)\right) > A^{1/2}$ and $PJ > 1$

4. We now show that $\frac{\partial m^*}{\partial \alpha} > 0$

   $\frac{\partial m^*}{\partial \alpha} = \frac{1}{2\beta}A^{-1/2}\frac{\partial A}{\partial \alpha}$. Since, $\frac{\partial A}{\partial \alpha} = 2\beta^2$, $\frac{\partial m^*}{\partial \alpha} = \beta A^{-1/2} > 0$

5. $\frac{\partial m^*}{\partial P} = \frac{A^{-\frac{1}{2}}}{2\beta}\frac{\partial A}{\partial P} = A^{-\frac{1}{2}}J\left[\left(1-\beta(1-PJ)\right) + \beta PJ\right] > 0$

6. We now show that $\frac{\partial \Phi}{\partial P} > 0$

   $\frac{\partial \Phi}{\partial P} = m^* + P\frac{\partial m^*}{\partial p}$. Since $\frac{\partial \mathrm{m}^*}{\partial P} = A^{-\frac{1}{2}}J\left[\left(1-\beta(1-PJ)\right) + \beta PJ\right] > 0, \frac{\partial \Phi}{\partial P} > 0$

7. We now show that the effect of P on Ω is non-monotonic.

$\frac{\partial \Omega}{\partial P} = -m^* + (1-P)\frac{\partial m^*}{\partial P}$. Since $\frac{\partial \mathrm{m}^*}{\partial P} = J(1-\beta)A^{-\frac{1}{2}} > 0$,

$$\frac{\partial \Omega}{\partial P} = -\left(1-\frac{1}{\beta}\right) + \frac{A^{\frac{1}{2}}}{\beta} + (1-P)\,J(1-\beta)A^{-1/2}$$

Rearranging terms, $\frac{\partial \Omega}{\partial P} = (1-\beta)\left(\frac{1}{\beta} + \frac{J(1-P)}{A^{1/2}}\right) - \frac{A^{1/2}}{\beta}$

$\frac{\partial \Omega}{\partial P} > 0$ if $(1-\beta)\left(\frac{1}{\beta} + \frac{J(1-P)}{A^{1/2}}\right) > \frac{A^{1/2}}{\beta}$ or when $(1-P) > \frac{A^{1/2}}{\beta J}\left[\frac{A^{1/2}}{1-\beta} - 1\right]$ and $\frac{\partial \Omega}{\partial P} < 0$ otherwise. Thus for high values of P, Ω is decreasing in P, while for high values of P, it is increasing in P.

Note that since $A^{1/2} > 1-\beta$, it is $\frac{A^{1/2}}{1-\beta} - 1 > 0$.

8. We now show that $\frac{\partial^2 \Omega}{\partial \alpha \partial P} < 0$

First, $\frac{\partial \Omega}{\partial \alpha} = \frac{\beta}{A^{\frac{1}{2}}}(1-P) > 0$

$$\frac{\partial^2 \Omega}{\partial \alpha \partial P} = -\frac{\beta}{A^{\frac{1}{2}}} - \frac{(1-P)\beta A^{-3/2}}{2}\frac{\partial A}{\partial P}$$

Since

$\frac{\partial A}{\partial P} = 2\beta J\left[\left(1-\beta(1-PJ)\right) + \beta PJ\right] > 0, \frac{\partial^2 \Omega}{\partial \alpha \partial P} = -\frac{\beta}{A^{\frac{1}{2}}}\left[1 + \frac{\beta J(1-P)\left[\left(1-\beta(1-PJ)\right)+\beta PJ\right]}{A}\right] < 0$

9. We now show that $\frac{\partial^2 \Phi}{\partial \alpha \partial P} > 0$

$\frac{\partial^2 \Phi}{\partial \alpha \partial P} = (1-P)\frac{\partial^2 m^*}{\partial \alpha \partial P} - \frac{\partial P}{\partial \alpha}\frac{\partial m^*}{\partial \alpha}$. Also $\frac{\partial^2 \Omega}{\partial \alpha \partial P} = P\frac{\partial^2 m^*}{\partial \alpha \partial P} + \frac{\partial P}{\partial \alpha}\frac{\partial m^*}{\partial \alpha}$

This implies that $\frac{\partial^2 \Omega}{\partial \alpha \partial P} + \frac{\partial^2 \Phi}{\partial \alpha \partial P} = \frac{\partial^2 m^*}{\partial \alpha \partial P}$ or $\frac{\partial^2 \Phi}{\partial \alpha \partial P} = \frac{\partial^2 m^*}{\partial \alpha \partial P} - \frac{\partial^2 \Omega}{\partial \alpha \partial P}$

Note that $\frac{\partial m^*}{\partial P} = J(1-\beta)A^{-\frac{1}{2}}$ and $\frac{\partial^2 m^*}{\partial P \partial \alpha} = -\frac{A^{\frac{1}{2}}}{2}.\frac{\partial A}{\partial P}.\beta$

With $\frac{\partial A}{\partial P} = 2\beta J\left[\left(1-\beta(1-PJ)\right)+\beta PJ\right]$, $\frac{\partial^2 m^*}{\partial\alpha\partial P}$=$[(1-\beta(1-PJ)+\beta PJ]\left(\frac{\beta(1-A\beta)}{A^{1/2}}\right) > 0$

Since A<1 and β≤1. Since $\frac{\partial^2\Omega}{\partial\alpha\partial P} < 0$, $\frac{\partial^2\Phi}{\partial\alpha\partial P} > 0$

10. $\frac{\partial m^*}{\partial\beta} < 0.$

Recall that $m^* = \left(1-\frac{1}{\beta}\right)+\frac{A^{\frac{1}{2}}}{\beta}$.

$$\frac{\partial m^*}{\partial\beta} = \frac{1}{A^{\frac{1}{2}}\beta^2}\left[A^{1/2} - A + \beta.\frac{\partial A}{\partial\beta}\right]$$

$$\frac{\partial A}{\partial\beta} = -2(1-PJ)\left(1-\beta(1-PJ)\right)+4\beta\left(\alpha-\frac{P^2J^2}{2}\right)$$

$$\frac{\partial m^*}{\partial\beta} = \frac{1}{A^{\frac{1}{2}}\beta^2}\left[A^{1/2}-(1-\beta(1-PJ))\right]$$

Since $\left(1-\beta(1-PJ)\right) > A^{1/2}$, $\frac{\partial m^*}{\partial\beta} < 0$

11. $\frac{\partial\Phi}{\partial\beta} = \frac{\partial m^*}{\partial\beta}P < 0 \; and \; \frac{\partial\Omega}{\partial\beta} = (1-P)\frac{\partial m^*}{\partial\beta} < 0$