Cash-out or flame-out: How does entrepreneurial opportunity cost influence entrepreneurial strategy? Empirical evidence from the information security industry

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Abstract:

We empirically study how opportunity cost of entrepreneurship conditions entrepreneurial performance. We assume that entrepreneurs in high tech startups aim to "cash out", by being acquired on favorable terms or through an IPO. Entrepreneurs with few alternative opportunities will tend to linger on as long as they can in the hopes of cashing out, whereas those with plentiful opportunities have a higher opportunity cost of staying on in the industry. These high opportunity cost entrepreneurs will attempt to cash out quickly or leave. We provide two simple models that formalize this intuition. Using a novel dataset of information security startups we find that entrepreneurs with high opportunity costs are not only more likely to succeed or cash-out but they are also more likely to fail and leave the industry.

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[1] This paper is taken from a chapter of Anand Nandkumar's 2008 PhD dissertation at The Heinz School, Carnegie Mellon University.

1 Introduction

Prior research has shown that opportunity costs play a key role in the decision of potential entrepreneurs to select into self-employment (Amit, Muller, and Cockburn, 1995; Reynolds,1987; Hamilton, 2000; Evans and Leighton ,1989; Clark and Drinkwater,2000;Gentry and Hubbard, 2000). Individuals with have better alternatives have higher opportunity costs of entrepreneurship and are less likely to select into entrepreneurship (Bhide *et al.*, 2000). However, little attention has been paid to how opportunity costs of entrepreneurship conditions the decision to remain in entrepreneurship.

Although its limitations are widely acknowledged, 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. Hence, relative differences in how long a firm survived in an industry are interpreted as differences in subsequent performance. However, in high tech industries, being acquired on favorable terms is at least one important objective of many high tech startups. Further, many startups have prominent founders, who have many outside opportunities. These high opportunity cost entrepreneurs are often impatient, preferring to leave and try their hand at something else (including perhaps a different startup), rather than linger on in the industry.

In this paper, we distinguish between two possible outcomes for a startup. It can either fail (e.g., if 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" in that if neither happens, the firm merely survives for another period. Thus, we break from the literature by treating survival (without an IPO) not desirable per se. Instead, survival merely keeps alive the option of trying for a payday.

We develop a simple model formalizes this intuition, and in the appendix, sketch out another model that leads to similar predictions. The entrepreneur has an idea whose quality is uncertain. The entrepreneur can make costly investments that provide signals about the quality of the underlying idea, and the precision of the signal can be improved by greater investment. We assume that the signal is public, so that the realization of a positive signal leads to a "cash-out". In addition to investing in a signal, the entrepreneur also decides when to leave the industry. In the model, this happens when the posterior probability is too low to justify the opportunity cost of staying on. It is easy to show that a high opportunity cost entrepreneur will make larger investments but will also leave the industry sooner.

In the appendix we sketch out another model with a different structure (e.g., the signal does not lead to a cashout, but instead demands investment in scale up, which increases the probability of a cash-out). In either case, we find that high opportunity cost entrepreneurs take actions that either hastens success and failure.

The investment taken to learn about the quality of the idea is arguably 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. In our model, instead of a cash constraint, a high burn rate which does not result in a positive signal lowers the posterior probability that the underlying idea is good. This leads the firm to quit.

We test this intuition using a novel dataset of startups that entered the information security market (ISM) from 1989 through 2004. Using data collected on founder histories, we construct measures of opportunity costs and exploit the variation in opportunity costs between firms, to examine how opportunity costs influence the subsequent performance of startups.

Controlling for quality of the firm and differences in firm capabilities, we find empirical support for our hypotheses.

This paper is organized as follows. The following section provides a brief overview of the literature. In section 3, we develop conjectures that we test empirically in section 5. In section 4, we explain the data sources that we for our empirical analysis. We conclude in section 6, with a discussion of the implications and proposed modifications to this working paper.

2 Literature

The empirical literature has thus far only examined how opportunity costs influences selection into entrepreneurship. 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) and, Evans and Leighton, (1989) show that entrepreneurs with higher opportunity costs are less likely to select into entrepreneurship.

However, the empirical literature on the relationship between pre-entry experience and subsequent performance of the firm (mainly measured as survival) is mixed. A section of the literature concludes that pre-entry experience is valuable and aids survival. 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). Thus if pre-entry experience is a proxy for opportunity costs of the founder, these results suggest that startups founded by entrepreneurs with higher opportunity costs, perform better.

These results are in direct contrast to another set of empirical results in the literature that provides evidence of higher failure rates among firms started by experienced entrepreneurs. The literature has rationalized these results by concluding that although all entrepreneurs are over-optimistic and overestimate potential returns from entrepreneurship (Landier and Thesmar, 2005), experienced entrepreneurs tend to be more overoptimistic than average and tend to fail more relative to others (Friedman, 2007; Camerer and Lovallo, 1999; Landier and Thesmar, 2005). This stream of work use over-optimism to justify another set of puzzling results: that of persistence of entry into entrepreneurship despite entrepreneurship not being relatively more profitable (see Hamilton, 2000, or, Moskowitz and Vissing-Jorgenson, 2002 for example).

We argue that one reason for the mixed evidence is the use of survival as a measure of performance. Instead, if the objective is to cash out, then survival represents the potential to do so. Furthermore, some firms may no longer survive because they were acquired at a premium, a typical mode of cash-out. Therefore, in this paper, we do not treat survival as evidence of good performance but directly measure whether the firm has cashed out or not, and also distinguish favorable acquisitions from failure.

Two measurement related advances enable us to systematically examine how opportunity costs influence entrepreneurial strategy and hence entrepreneurial outcomes. First by matching our dataset of startups (explained in detail, later) with M&A and IPO database, we are able to distinguish between failure and cash-outs. Second, by gathering detailed data on founder histories we are able to develop empirical proxies for the opportunity costs of entrepreneurs.

3 Model

As described earlier the goal is to identify how opportunity costs of entrepreneurship conditions both success and failures, and also how opportunity costs condition how early such success or failures are likely to happen. We develop a simple model to guide the empirical analysis. We should also stress that this model is one of several possible models that could be used and 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 resolution of uncertainty about the underlying potential of their nascent business.

Opportunity costs and "burn rates"

We assume that there are two opportunities, "blockbuster", and "poor". A poor opportunity yields zero cash-out. In any period that a firm operates, a blockbuster opportunity results in a cash out that results in a payoff of J with probability m, with a corresponding burn rate of c(m) per period, where c(m) is increasing and convex in m. The firm (entrepreneur) has an opportunity cost of α for every period it operates. The firm is uncertain about the nature of the opportunity but has a prior P_B that it has a blockbuster opportunity. A firm chooses how long it stays in the market and its burn rate. We assume that the burn rate cannot change from period to period.[2] Finally, there is no time discounting – all of that is captured in α.

At the time of entry it is unlikely that entrepreneurs know whether the opportunity is a profitable one or not. However, an entrepreneur can take actions to resolve this uncertainty sooner than later. For instance an entrepreneur can invest in market research, or invest in a larger sales and marketing force, or develop a more complete product or solution in order to understand if the opportunity is in fact viable or not. Such an investment implies that an entrepreneur invests more in the short run, popularly referred to as "burn rates" in trade journals. However, such investments are likely to provide a better signal of whether or not the entrepreneurial opportunity is a profitable one or not. Moreover, higher investments associated with a more accurate signal -

[2] Allowing m to vary according to the period will complicate the analysis but should yield similar results.

for example, market research over a larger sample audience, although very expensive, provides a more accurate sense of whether a product or a service is likely to succeed or not.

The probability that an entrepreneur succeeds in period t, given that it has not succeeded in period t-1 , is just mP_B. The probability that an entrepreneur succeeds in the nth period is just $m(1-m)^{n-1} P_B$. Thus the expected profits of an entrepreneur with an opportunity cost of α per period is given by $\Pi \equiv mJP_B(1+(1-m)+\ldots+(1-m)^{n-1}) - nc(m) - n\alpha$ which is just

$$\Pi \equiv JP_B(1-(1-m)^n) - nc(m) - n\alpha \quad (1)$$

Let m^* and n^* be the optimal values of *m* and n respectively. The first order conditions for an interior optimum (ignoring that n is an integer) are

$$\frac{\partial \Pi}{\partial n} = -JP_B\left((1-m)^n \ln(1-m)\right) - c(m) - \alpha = 0 \quad (2)$$

$$\frac{\partial \Pi}{\partial m} = -JP_B n(1-m)^{n-1} - nc'(m) = 0 \quad (3)$$

Note that $\ln(1-m) < 0$ because $1-m < 1$. Notice also that the marginal payoff to *m* is unaffected by α. Thus, the impact of α on *m* will be determined by whether *m* and n are strategic complements or substitutes (cf. Milgrom and Roberts, 1990). Observe that evaluated at the optimum point, *m* and n are strategic substitutes, because the cross partial (4) evaluated at the interior optimum is negative. The cross partial is

$$\frac{\partial^2 \Pi}{\partial n \partial m} = nJP_B(1-m)^{n-1} \ln(1-m) - c'(m) + JP_B(1-m)^{n-1} \quad (4)$$

Substituting (3) in (4), we get that the cross partial evaluated at the interior optimum

$$\frac{\partial^2 \Pi}{\partial n \partial m} = nJP_B(1-m)^{n-1} \ln(1-m) < 0$$

Assuming that the necessary conditions are sufficient, the following results follow directly

Result 1: m^* is increasing in α and n^* is decreasing in α. Entrepreneurs with higher opportunity costs have higher burn rates and a smaller time frame to evaluate an idea.

Proof:

$\frac{\partial n}{\partial \alpha} < 0 \Leftrightarrow -\frac{\partial^2 \Pi}{\partial n \partial \alpha}\frac{\partial^2 \Pi}{\partial m^2} < 0 \Leftrightarrow \frac{\partial^2 \Pi}{\partial n \partial \alpha} < 0$. By direct calculation, $\frac{\partial^2 \Pi}{\partial n \partial \alpha} = -1 < 0$

$\frac{\partial m}{\partial \alpha} > 0 \Leftrightarrow \frac{\partial^2 \Pi}{\partial n \partial m}\frac{\partial^2 \Pi}{\partial n \partial \alpha} > 0$. We have already shown that the first term on the right is negative and the second is negative as well, leading to the result.

This result formalizes that intuition that entrepreneurs that have higher opportunity costs have a lower time frame to evaluate an opportunity, and also have higher initial investment, or, burn rates.

Hazard of cash-out

The probability of success in a period conditional on staying in the industry is just $\Phi \equiv mP_B$. As we have shown that *m* increases with α, it follows directly that the hazard of a cash out is increasing in opportunity cost.

Prediction 1: Φ is increasing in α. Entrepreneurs that have higher opportunity costs have a higher hazard of cash out.

Hazard of failure

In this model, the probability that a firm fails in period t is zero for $t \le n$, and 1 otherwise. Therefore, it follows trivially that the hazard of failure is weakly higher for high opportunity cost firms.

Prediction 2: The hazard of failure is greater for high opportunity cost entrepreneurs.

Note that a different way of stating this is that high opportunity cost entrepreneurs have shorter industry tenures. In conventional survival estimation, this would result in lower estimated survival rates. Gimeno *et al.*, 1997, for instance finds that more experienced entrepreneurs actually have higher hazards of exiting an industry and conjectures that one of the reasons that the finding might be true is because, more experienced entrepreneurs might have higher "threshold" profitability or higher opportunity costs.

<u>Time to failure, conditional on failure</u>

Since firms that fail, fail in period n, and since n is smaller for high opportunity cost firms, it follows that when they fail, high opportunity cost entrepreneurs will fail earlier than low opportunity cost firms.

Prediction 3a: Conditional on failure, the time to failure is lower for high opportunity cost firms.

<u>Time taken to cash-out conditional on cash-out</u>

Let t represent the time of a cash-out. The probability that the firm cashes out by period t, given that it has cashed out, $Pr(r \leq t | r \leq n) = (1-(1-m)^t)/ (1-(1-m)^n)$. It can also be shown that the expression is increasing in m. Further, the probability is decreasing in *n.* Thus, the probability distribution of cash-out times for firms that cash out shifts to the left (a first order stochastic dominance shift). It follows that the expected time to cash out is diminishing with α, the entrepreneurial opportunity cost.

Prediction 3b: Conditional on cash-out, the time to cash-out is lower for high opportunity cost firms.

<u>Overall probability of failure and cash-out</u>

Notice that we cannot determine whether higher opportunity cost firms have a greater overall probability of cash-out or not. This is because the two decisions work in opposite directions – a higher burn rate increases the probability of cash-out (for a given prior) but the lower *n* gives the firm fewer chances. The net effect is, quite appropriately, uncertain.

Opportunity costs and quality of entrepreneurial ideas:

With an eye towards the empirical analysis, it is plausible that high opportunity cost entrepreneurs may also be more capable entrepreneurs. This may be reflected in several ways. First, they may have access to higher quality opportunities. In terms of our model, we would represent this as an increase in P_B. More capable entrepreneurs may also be able to extract more value from a given opportunity, implying a higher J. Both of these would, in general, increase both m and n. Finally, a more capable entrepreneur may also be able to extract more information in an uncertain situation. She may know lead adopters of the innovation and may be able to conduct market experiments more effectively. In our model, this would be captured by a reduction in c'(m) i.e., in the marginal cost of increasing the probability of cash-out. This would imply an increase in *m* and a decrease in *n,* further reinforcing our results. In view of these divergent effects, it will be crucial in our empirical analysis to have controls for the capability of the firm as well controls for the initial quality of the opportunity. In line with the literature, we use (log) initial scale to control for the underlying quality of the firm and use two different proxies (explained later) for opportunity cost. As proxy of opportunity cost is inevitably also likely to also be correlated with the ability of the entrepreneur, we control for the initial quality of the idea, so that variation in our measure of opportunity cost is likely to pick up differences in opportunity costs rather than differences in ability.

4 Data and measures

Our sample for the purposes of this study consists of 286 ISM startups, followed from the time of entry till 2004 or their exit (cash-out or failure), whichever is earlier. The ISM is a rapidly growing segment in the computer industry that consists of several submarkets (Arora and Nandkumar, 2007). From the Corptech directory, we first 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) of security startups 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. The data on founders also include the number of years of experience (referred to founder's experience, henceforth) of each founder of a firm, calculated from the time of last graduation, until the year of founding of the firm in question. For firms with multiple founders, the founder with the greatest work experience was designated as the main founder and his or her characteristics were then used to characterise the startup.

We classified founders into the following cateogries: related founders (former employees of computer hardware, software, telecommunication or ISM firms), unrelated founders (former employees from defense, finance, aerospace and automobile industries), university founders, consultants, hackers[3], and others. As table 1, shows entrants into the ISM were of diverse origins. About 52% of the startups were related startups and about 26% of the startups were unrelated startups. About 7% of the startups were serial startups and the remaining comprised of other startups.[4]

Table 1- Sources of entry in ISM

Entrant type	ISM	Mean prev. jobs	Mean work exp.(yrs)
Others[a]	18%	1.72	2.69
		(0.19)	(1.05)
Related startups	52%	3.67	12.70
		(0.17)	(0.98)
Unrelated startups	26%	2.41	4.52
		(0.45)	(1.25)

[3] Firms were identified as hackers founded startups if the firm the following criterion: the firm had at least one founder that unemployed immediately prior to founding the ISM startup.
[4] Founder backgrounds for 29 firms could not be traced.

Serial	7%	2.56 (0.19)	7.91 (2.52)

Notes: The total proportion adds up to more than 100% because many firms have multiple founders
[a] Includes hackers, or founders with no experience and university founders

Failure: Firms in the sample exited either due to two reasons: non viability of the business (failure) or acquisition by another firm (merger). These were coded separately in the dataset. We identified a startup as having failed if the focal startup ceased to exist as a separate firm and was not acquired on favorable terms. Thus implicitly, distress acquisitions were also treated as failures.[5] We identified the year of failure as the year in which, the corporate 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 acquisition (asset sale) was year in which it was acquired.

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

Time to failure is the number of years from the year of entry till failure.

Time to cash-out is the number of years in the ISM from the year of entry until cash-out.

Measures of 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 profession. Given the infeasibility of developing such a measure we develop two

[5] 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, which was determined using the language of the press release of the acquisition. 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). Mergers that failed both these criteria were treated as a successful merger. A total, of 79 firms in our sample were acquired, of which 11 of the acquisitions were classified as being distress. A different method which yields very similar results is if we categorize all cases where the firm is sold for less than $1 million as a distress sale.

proxies for opportunity costs. The first measure of opportunity costs is the number of organizations (just previous jobs henceforth) that the main founder of the startup, worked in after graduation. 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 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.

Our measure of opportunity costs have obvious limitations. For instance previous jobs apart from capturing opportunity costs may also capture 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 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).

Our second 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. We then use the amount of work experience of the founder that had maximum work experience among all founders of the startup, as one of our measures of opportunity cost. This measure relies on work experience on an average being positively correlated with higher wages in paid employment. 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. Also, more experienced entrepreneurs are also likely to have many other alternatives besides running a firm. Note however that the two measures are highly correlated (corr – 0.64).

In addition we also use the following as controls in our regressions.

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 entry. We collected this variable by using a keyword search on the US PTO trademarks database (http://tess.uspto.gov).[6] In cases where the startup had multiple parents, we use the number of IT trademarks of the parent that had the maximum number of IT trademarks among all the parents of the startup.

Technical capability: We use the number of information security patents by any of the founders, as well as any patents assigned to the startup when it was formed. For all sample firms, we collected the number of ISM patents from the US.PTO database. These are patents that belong to the US patent technological classes 705 subclass 50-79, 380 and 726. As is standard in the literature, in the empirical analysis, instead of using raw patent counts, we use the information security patent counts, weighted by the number of forward citations.

There are obvious and well known limitations of patents as a measure of technical capability. Not all technology is patentable or patented. Clever virus researchers for instance, infrequently produce patentable technology. Instead, competitive advantage relies on the early discoveries of viruses and other types of malware and then the development of ways to detect and block them. In turn this may require the ability to constantly monitor the relevant Internet

[6] 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 ").

activity and a deep knowledge of the hacker community. Accordingly, we use both market 7 segment fixed effects, one for each segment in our empirical analysis.

ISM tenure: 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. It is well known that survival is time dependent – firms that survive for a certain number of years are likely to survive longer (Dunne, Roberts, and Samuelson, 1988; Evans, 1987; Audretsch and Mahmood, 1995;Mata and Portugal,1994). In other words, hazard rates are not independent of how long the firm has survived. To control for this, in regressions that use survival or time to cash-out as the dependent variable, we control for how long the firm has survived using ISM tenure, which is the number of years a firm has been in the ISM. To allow for non-linearities, we also include the square term.

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

Entry Cohorts: As discussed, the demand for information security prior to the Internet was limited and the growth of the Internet provided a great boost to demand. The boom years were also a time of great entrepreneurial experimentation and it plausible that firms that entered during that period were different from those that preceded them. After the collapse of the Internet bubble, it is plausible that financing and survival for Internet focused companies became harder. Accordingly, we distinguish between *when* the firm entered, using three time periods: Prior to the Internet (1980-1995), Internet boom years (1996-2000), and post bubble (2001-2004).

Entrant type: We classified startups into one or more of the following categories based on the immediate prior experience of founders:, *related startups* (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.

ISM submarket dummies: In all our empirical specifications we also distinguish between the different ISM submarkets that startups entered by including 7 submarket dummies one each, for the following submarkets: encryption product, network security, authentication , firewalls, antivirus, spam control, hardware submarkets. Consulting is the residual category.[7] In some specifications, we collapse these into two groups. The first group, called the encryption based segment dummy takes a value of 1 if the focal firm entered encryption products, network security, and authentication segments and 0, if the focal firm entered firewalls, antivirus, spam control, hardware, or consulting segments. We use this in to control for differences between encryption based technologies and other information security technologies only in certain specifications in place of ISM submarket dummies to conserve degrees of freedom.

Source of capital dummies: In many of our specifications we also control for the source of capital of startups. We distinguish between three funding sources – venture capital (using VC dummy) and corporate venture capital (using CVC dummy). The residual category comprises of startups that were self-funded by entrepreneurs. The funding is measured at the time of entry and is self-reported.

Initial scale: We also control for the initial scale of entry measured as the number of employees employed by the focal startup at the time of entry into the ISM. The prior literature has argued

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

that initial size of firms is a reasonable proxy for the quality of startups (Mata and Portugal, 1994; Agarwal and Audretsch, 2001). 35 startups do not report their initial scale.

Measure of burn rate: We use several proxies for "burn rate". The one featured in the regressions is the live products (just products, henceforth) held by the focal startup, at end of two years from entry. Another potential measure is simply growth in employment after entry at end of two years from entry (corr. between the two measures is 0.69)

Table 2 Description of measures used

Variable	**Description**	Source of variation	N	Mean	Std. Dev
Failure	=1 if the startup was acquired on unfavorable terms, or went out of business.	Firm	286	0.23	
Cash-out	=1 if the startup merged on favorable terms or had an IPO even whichever is earlier	Firm	286	0.20	
Log(1+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(1+prev. jobs)	Log of 1+ # number of previous jobs of the main founder. This is another proxy for opportunity cost.	Firm	279	0.46	0.74
Log(products)	Log of # products or services offered in the first two years after entry. This is a proxy for initial investment z	Firm, year	558	0.45	0.43
Time to failure	Calculated as year of failure – year of entry		76	1.77	0.76
Time to cash out	Calculated as year of cash out – year of entry	Firm	56	1.73	0.72
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 starup at entry.	Firm	286	1.07	1.89
Industry age	Age of the industry measured from 1970		286	8.87	5.68
ISM tenure	Calculated as current year – ISM entry year		286	6.88	4.94
Related startups dummy	=1 if the founder was from ICT industry, ISM or a consultant.		286	0.52	-
Unrelated startups dummy	=1 if founder was a hacker or a university professor prior to entering the ISM		286	0.26	-
Serial startups dummy	=1 if the founder was a serial founder		286	0.07	-

Entry cohort dummy variables	Three dummy variables that indicates if the startup entered in the pre-internet era, boom years or post bubble				
VC dummy	=1 if the focal startup was funded by venture capital	Firm	286	0.34	0.47
CVC dummy	=1 if the focal startup was funded by corporate venture capital	Firm	286	0.05	0.21

[a] Founder histories for 7 startups could not be traced. Of these 3 report initial scale while 4 report initial scale.
[c] 35 startups do not report their initial size.

5 Empirical analysis

Our main results use the number of previous jobs of the main founder as a proxy for opportunity cost. The unit of observation is an ISM startup.

We begin with providing descriptive statistics from the data. We first show that startups that had high employee growth rates, a proxy for initial investment or "burn rate", in the first two years of operation had more experienced founders. Moreover, in line with our conjectures, we also show that while a proportion of startups cashed-out, many of them failed as well. However, the overall cash-out as well as failure rates among startups that grew rapidly over the first two years was higher than the sample average cash-out and failure rates.

Table 3 shows that there were a total of 158 startups that grew by over 100% in either of the first two years had founders with an average of 3.7 prior jobs. The remaining (slow growing firms) had founders with an average of 1.24 jobs. About 25% of these firms (40 in all) were successful and about 29% failed (46 firms). Comparing these numbers with descriptive statistics shown in table 2, suggests both the success and failure rates were relatively high in comparison to the average success and failure rates (20% and 23% respectively).

Table 3 Description of measures used

Avg. growth rate in the first two years	N	Prev. jobs
>100% in any or both years in 2 years from entry	158	3.70 (1.72)
≤100% in any or both years in 2 years from entry	128	1.24 (1.18)

>100% in any or both years in 2 years from entry and cashed out	40	3.79 (1.52)
>100% in any or both years in 2 years from entry and failure	46	3.37 (1.63)

Next, we provide some non parametric analysis of the data. In table 4 we show that, startups founded by entrepreneurs high opportunity cost (above average number of prior jobs) (High) have higher initial scale make higher initial investments relative to startups founded by entrepreneurs with less than mean number of previous jobs (low). With the number of products in the first two years from entry as a proxy for initial investment, row 2 of table 4, shows that entrepreneurs founded by entrepreneurs that had had more previous jobs, have more product lines than those founded by entrepreneurs with lower previous jobs (0.55 vs. 0.44). This result is consistent with our hypothesis that entrepreneurs that have higher opportunity costs are likely to have higher burn-rates.

Table 4 – Growth in product line, scale up investment, failure rates, cash-out rates and tenure by high and low opportunity cost (prev. jobs) (std. errors in parentheses)

	High OC (1)	Low OC (2)	Difference (1)-(2)
Number of Products after 2 years (in log)	0.55 (0.02)	0.44 (0.03)	0.11 (0.03)
Failure	0.24 (0.02)	0.18 (0.01)	0.06 (0.02)
Cash-out	0.27 (0.01)	0.23 (0.04)	0.04 (0.04)
Tenure conditional on failure (yrs.)	6.20 (0.87)	8.40 (0.95)	2.20 (1.28)
Tenure conditional on cash-out (yrs.)	5.12 (0.94)	8.00 (1.08)	2.88 (1.43)

Table 4, shows that, entrepreneurs with higher opportunity costs, are not only more likely to fail (0.28 vs. 0.22), but are also more likely to cash-out as well (0.27 vs. 0.23). Moreover the last two rows of table 4, shows that entrepreneurs with higher opportunity costs have shorter tenures conditional on failure or cash-out relative to entrepreneurs that have lower opportunity costs (6.20 vs 8.40; 5.12 vs. 8.00). All these are consistent with our model.

The non-parametric analysis above supports our hypotheses, but does not control for a variety of other factors. We start with testing our hypothesis that relates to burn rates. To this end, we use OLS, in which the dependent variable is products (in log).[8] Our main independent variable of interest is the number of (log 1+) previous jobs. We control for the technical and marketing ability of a startup using log (patents) and log(parent IT trademarks). We also control for the type of entrant and ISM market using entrant type and sub-market dummies. Finally, we also control for entry cohort effects using 2 cohort dummies. Results are presented below in table 5.

Table 5 – OLS regressions of burn-rate

	Spec. 1 Dep. Var – log(products)
Log(1+ prev. jobs)	0.20 ***
	(0.03)
Related startup dummy	0.15 ***
	(0.04)
Unrelated startup dummy	0.01
	(0.10)
Serial entrepreneurs dummy	0.21 ***
	(0.06)
Venture funded dummy	0.08 **
	(0.03)
Corp. VC funded dummy	0.09 ***
	(0.01)
Log(patents)	0.18 ***
	(0.02)
Log(parent IT TM)	0.14 *
	(0.08)
Constant	0.20 ***
	(0.04)
N	558[a]
No. of firms	279
Adj. R^2	0.24

[8] Using employee growth, in the first two years as a dependent variable, yields qualitatively similar results.

Submarket dummies(7)	Y
Entry cohort dummies (2)	Y

Notes: Standard errors in parentheses, cluster corrected by firm.***Significant at 1%. ** Significant at 5%. * Significant at 10%. Unit of observation firm, year. [a] Consists of 1 observation per firm per year for 279 firms, over 2 years.

Specification 1 of table 5, suggests that firm started up by entrepreneurs with high opportunity costs are likely to have larger initial investments, or burn rates: using sample means, two and half times increase, or an increase in the number of previous jobs by about 4, is associated with about an additional product line. This estimate is statistically significant at 1% level. This estimate is consistent with result 1. Interestingly, serial entrepreneurs on an average are likely to have higher initial investments relative to other entrepreneurs and so do firms with higher technical ability (firms that have higher security patents). Moreover, VC, as well as, corporate funded firms have higher initial investments.

We next empirically test our hypotheses that relate to the hazards of cashing out or, failure. In the context of our data there are two absorbing states that a startup can transition into, which are failure and cash-outs. Following Boyd *et al.*, 2005 we consider failure and cash-out as competing hazards and implement a discrete time hazard regressions specification that are widely used in the literature (Martin and Mitchell, 1998; King and Tucci, 2002).[9] In these regressions, the dependent variable takes a value of 1 if the focal startup had a failure event and 2 if there was a success event (cash-out) in the period of observation. The baseline option is to remain in the ISM. Our unit of observation is a firm-year.

Suppose $F_D(t)$ is the probability that a firms failure on or before time *t* and $F_C(t)$ the probability that a firm cashes out before time *t*. The probability that a firm is alive, $F_A(t)$ is just

[9] Results of a continous time hazard models yield qualitatively similar results. For instance the results of Cox proportional hazard specifications that estimates the hazard of exit and cash-outs separately, yield qualitatively similar results.

$(1- F_D(t))*(1- F_C(t))$, or the survival probabilities is just $S_D(t)*S_C(t)$, where $S_D(t) = (1- F_D(t))$ and $S_C(t) = (1- F_C(t))$.

Define $f_D(t)$, $f_C(t)$, $f_A(t)$ as the probabilities that a firm fails or cashes out at time *t*. Each one of these are just the derivatives with respect to *t* of their corresponding cdf's described above. The hazard of failure at time *t*, $h_D= f_D(t)/ S_D(t).S_C(t)$ (note that the denominator is just the probability of not failing and not cashing out in which case firms drop out of the sample). Similarly, the hazard of cash out is $h_C= f_C(t)/ S_D(t).S_C(t)$ and the hazard of staying alive, $h_A= f_A(t)/ S_D(t).S_C(t)$. This implies that $h_C/ h_A= f_C(t)/f_A(t)$ and that $h_D/ h_A= f_D(t)/f_A(t)$.

Suppose we assume that the payoff if the firm *i* stays alive in year *t* is $P_{it}^A+e_{it}$. Similarly suppose its payoff if it cashes out is $P_{it}^C+e_{it}$ and the payoff it fails is $P_{it}^D+e_{it}$. Assuming that e_{it} is gumbel distributed we will get a multinomial logit model, which of course suffers from the problem of IIA. In order to solve this problem, as proposed by Heckman and Singer, (1984) we add a random error term u_{it}. Now the probability that a firm chooses to stay alive, is $\Pr(P_{it}^A+e_{it} > \max(P_{it}^D+e_{it}, P_{it}^C+e_{it}))$ which is just $f_A(t \mid u) = \frac{\exp(P^A{}_{it}; u^A{}_{it})}{1+\sum_H \exp\left(P_{it}{}^H; u^H{}_{it}\right)}$ where H= failure or cash out. This is just the multinomial logit model subject to the random error term. The unconditional probability can be got by just integrating out the u term. Following Heckman and Singer, (1984) we assume that u has a discrete distribution and estimate that discrete distribution non-parametrically. Note that our regressions are estimated assuming a random error term at the level of a firm and sub-market. We assume that the random error term, has a two point mass that is also estimated. We hence estimate 2 masses and the 2 location parameters as well. We use the gllamm procedure in stata 10 to estimate our regressions

Note that a startup essentially remains in the sample until it fails or cashes out, whichever is earlier. In all 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. We exclude observations relating to 35 firms since these firms did not report their initial scale. We also further drop observations that relate to 4 more firms because data on previous jobs was not available. Since VC dummy and CVC dummy could be possibly endogenous to failure or cash-out, which are essentially measures of performance, we exclude these dummy variables in these specifications.[10] That the results of the specification that includes VC and CVC dummies are qualitatively similar to those that exclude these dummies, suggests that any endogeneity on account of including these dummies, if any does not significantly bias the coefficients of interest. The results are shown under specifications 1 and 2 of table 6.

Table 6 –Competing hazard regressions of failure or cash-out (standard errors in parentheses)[a]

	Spec. 1		Spec. 2	
	Failure	**Cash-out**	**Failure**	**Cash-out**
Log(1+ prev. jobs)	0.38 ***	0.61 ***	0.31 ***	0.66 ***
	(0.12)	(0.23)	(0.12)	(0.17)
Log (1+ patents)	-0.15	0.17 ***	-0.14	0.19 ***
	(0.10)	(0.05)	(0.13)	(0.08)
Log(1+parents IT TM)	-0.18 ***	0.14	-0.19 ***	0.16 *
	(0.02)	(0.10)	(0.03)	(0.09)
Log (scale)	-0.25 ***	0.71 ***	-0.20 ***	0.82 ***
	(0.11)	(0.20)	(0.08)	(0.23)
Related startups dummy	0.45 *	0.62 ***	0.46 *	0.62 ***
	(0.23)	(0.21)	(0.25)	(0.21)
Unrelated startups dummy	-0.21 ***	0.30	-0.19 **	0.30
	(0.04)	(0.50)	(0.08)	(0.50)
Serial entrep. dummy	0.49 **	0.97 ***	0.51 **	0.97 ***
	(0.23)	(0.56)	(0.26)	(0.56)
ISM tenure	-0.04 *	0.11 *	-0.04 *	0.12
	(0.02)	(0.07)	(0.02)	(0.06)
ISM tenure squared	-0.00 ***	-0.00 **	0.01	-0.01
	(0.00)	(0.00)	(0.01)	(0.00)
Industry age	-0.27 *	-0.25 *	-0.28 ***	0.48 *
	(0.15)	(0.16)	(0.13)	(0.28)

[10] For instance, expectations of profitability could influence whether or not a firm gets VC funded.

Industry age squared	-0.04 ***	0.03 ***	-0.03 ***	0.03 ***
	(0.00)	(0.00)	(0.00)	(0.00)
VC dummy			0.20 ***	0.43 ***
			(0.07)	(0.10)
CVC dummy			0.06	0.31
			(0.08)	(0.31)
Constant	-3.11 ***	-4.09 ***	-3.61 ***	-3.97 ***
	(0.30)	(0.28)	(0.34)	(0.31)
N	1998		1998	
No. of firms	247[b]		247	
LL	-345.43		-339.36	
Location parameter 1	1.35, -0.79		1.23, -0.66	
Location parameter 2	-0.38, 0.22		-0.34, 0.16	
Variance	0.51, 0.17		0.50, 0.21	
Covariance	-0.30		-0.33	
Probabilities	0.22, 0.78		0.19, 0.81	
Submarket dummies(7)	Y		Y	
Startup type dummies(3)	Y		Y	

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.

The results suggest that firms started up by entrepreneurs with higher opportunity costs are more likely to fail. For instance, from specification 1, in the failure equation, an additional previous job is likely to increase the relative hazard (relative to the baseline hazard) of failure by about 38%. Also in the failure equation, the coefficient of scale is negative and significant. Results of the cash-out equation in the same specification suggest that entrepreneurs with higher opportunity costs are more likely to cash out as well: an additional previous job is associated with about a 50% in the relative hazard of cashing out.

In the final set of regressions, we test if startups founded by entrepreneurs with high opportunity costs have shorter industry tenures. In order to do so, we implement two OLS regressions one with time to failure, (conditional on failure) as the dependent variable and another with time to cash-out (conditional on cashing out) as the dependent variable. Since we are conditioning on failure or cash outs, these regressions the sample comprises of exclusively firms that fail or cash out of the ISM. Accordingly while the regression that uses time to failure as the dependent variable use only 76 observations in all, the regression with time to cash-out as the dependent variable uses only 56 observations. We retain the same set of independent variables as in table 4 with two differences. In order to conserve degrees of freedom we do not distinguish between the 7 ISM submarkets but instead distinguish only between whether a particular ISM market is an encryption based market or not using an encryption dummy. We also do not control for technical and marketing capabilities of the startup, once again since we do not have enough observations. Results are shown in table 7.

Table 7 – OLS regressions of industry tenure

	Spec. 1 log(time to failure) | fail	**Spec. 2 log(time to cash-out)| cash out**
Log(1+ prev. jobs)	-0.13 **	-0.35 **
	(0.06)	(0.10)
Related startup dummy	-0.03	-0.27
	(0.08)	(0.48)
Unrelated startup dummy	0.38	0.37 ***
	(0.49)	(0.05)
Serial entrepreneurs dummy	-0.46 **	-0.21
	(0.08)	(0.15)
Venture funded dummy	-0.38 ***	-0.23 ***
	(0.13)	(0.03)
Corp. VC funded dummy	-0.94 ***	-0.64 ***
	(0.12)	(0.02)
No size dummy[a]	0.06	
	(0.27)	
(1-nosize)*Log(init. scale)	0.11 ***	
	(0.04)	
Log(init. scale)		-0.17 *
		(0.10)
Constant	1.44	1.56 ***
	(0.37)	(0.57)
N	76	56
No. of firms	76	56
Adj. R^2	0.49	0.55
Encryption market dummy	Y	Y
Entry cohort dummies (2)	Y	Y

Notes: ***Significant at 1%. ** Significant at 5%. * Significant at 10%. [a] In spec. 1 since, 12 startups do not report their initial scale we use a no size dummy variable.

Table 7 shows that conditional on failure, entrepreneurs with higher opportunity costs are likely to fail sooner: using specification 1, a 10% increase in the number of previous jobs is associated with about 1.3% shorter industry tenure, conditional on failure. Using sample means, one standard deviation increase in the number of previous jobs is associated with about 1.75 year shorter tenure in the ISM. Further specification 2, suggests that a 10% increase in the number of previous jobs is associated with about 3.5% shorter industry tenure. Once again using sample means, this implies that an entrepreneur with 1 standard deviation more previous jobs is likely to have a shorter tenure in the ISM by about 4 ½ years.

In summary, empirical estimates support the predictions of intuition formalized in section 3: Entrepreneurs that have higher opportunity costs are likely to make higher initial investments or are likely to have higher burn rates. Our results also confirm our hypotheses related to failure and cash-outs: higher opportunity cost entrepreneurs are not only more likely to fail but also cash-out. Moreover, conditional on cashing out entrepreneurs with higher opportunity costs are also likely to cash-out sooner. Similarly, conditional on failure, entrepreneurs that have higher opportunity are also likely to fail sooner. The final result highlights some of the problems that bedevil using survival as a measure of performance. For one, the results show that differences in rates of survival apart from reflecting differences in performance could also reflect differences in preferences to continue as entrepreneurs. Our results show that a factor that influences the preference to stay on, is the opportunity cost of entrepreneurs, of pursuing entrepreneurial activity.

Robustness checks

A. Alternative measure of opportunity costs: Since previous jobs may not adequately proxy for opportunity costs, we explore the robustness of our principal results using an alternative measure of opportunity costs, namely the amount of work experience, measured in years, of the main founder of the startup. We start by replicating specification 1 and 2 of table 4, in table 8.

Table 8 – OLS regressions of initial investment and scale up investment

	log(products)	
Log(1+ work exp.)	0.16	***
	(0.01)	
Related startup dummy	0.15	***
	(0.04)	
Unrelated startup dummy	0.06	
	(0.07)	
Serial entrepreneurs dummy	0.15	***
	(0.04)	
Venture funded dummy	0.05	*
	(0.02)	
Corp. VC funded dummy	0.07	***
	(0.02)	
Log(patents)	0.18	***
	(0.02)	
Log(parent IT TM)	0.10	***
	(0.05)	
Constant	0.28	***
	(0.06)	
N	558	
No. of firms	279	
Adj. R^2	0.23	
Submarket dummies(7)	Y	
Entry cohort dummies (2)	Y	

Notes: Standard errors in parentheses, cluster corrected by firm.***Significant at 1%. ** Significant at 5%. * Significant at 10%. Unit of observation firm, year.

Specification 1 of table 8 shows that one standard deviation increase in the amount of industry experience is associated with about a 10% increase in the number of product lines of the startup.

Table 9 –Competing hazard regressions of failure or cash-out (standard errors in parentheses)[a]

	Failure		Cash-out	
Log(1+ work exp.)	0.26	***	0.16	**
	(0.10)		(0.04)	
Log (1+ patents)	-0.22		0.20	
	(0.18)		(0.15)	
Log(1+parents TM)	-0.16	***	0.17	
	(0.05)		(0.13)	
Log (init. scale)	-0.26	***	0.72	***

	(0.11)		(0.22)	
Related startups dummy	0.46	**	0.74	*
	(0.21)		(0.45)	
Unrelated startups dummy	-0.22	***	0.14	
	(0.05)		(0.47)	
Serial dummy	0.50	*	0.62	***
	(0.21)		(0.15)	
ISM tenure	-0.04	*	0.14	**
	(0.02)		(0.06)	
ISM tenure^2	0.01		-0.01	*
	(0.01)		(0.00)	
Industry age	-0.26	*	-0.21	
	(0.15)		(0.15)	
Industry age^2	-0.03	***	0.01	**
	(0.00)		(0.00)	
Constant	-3.08	***	-4.21	***
	(0.33)		(0.26)	
N	1998			
No. of firms	247[b]			
LL	-333.32			
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			
Submarket dummies(7)	Y			
Startup type dummies(3)	Y			

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.

We next test the robustness of our results that relates to cash-out and failure using an alternative measure of opportunity cost. We replicate specification 1 of table 6, in table 9. As in the case of our principal results, table 9 suggests that firms started up by entrepreneurs with high opportunity costs not only have higher failure hazards but they have higher cash-out rates as well. A one standard deviation increase in the amount of work experience of the main founder increases the hazard of failure by about 16%. Moreover a one standard deviation increase in the amount of work experience of the main founder increases the hazard of cashing out by 11%. Finally we replicate the table 7, using the alternative measure of opportunity cost in table 10. Specification 1 of table 1 shows that a 1 standard deviation increase in the number of years of work experience is associated with about a 9% decrease in time to failure. Moreover specification 2, suggests that a 1 standard deviation increase in the amount of work experience is associated with about 18% decrease in time to cash out. Overall, these results are consistent with our principal results discussed earlier.

Table 10 – OLS regressions of industry tenure

	Spec. 1 Dep. Var – log(time to failure)		**Spec. 2 Dep. var – log(time to cash-out)**	
Log(1+ work exp.)	-0.07	***	-0.15	**
	(0.02)		(0.04)	
Related startup dummy	-0.05		-0.28	
	(0.06)		(0.41)	
Unrelated startup dummy	0.37		0.24	
	(0.49)		(0.14)	
Serial entrepreneurs dummy	-0.43	***	-0.31	*
	(0.09)		(0.14)	
Venture funded dummy	-0.40	***	-0.26	***
	(0.11)		(0.05)	
Corp. VC funded dummy	-1.00	***	-0.55	***
	(0.09)		(0.08)	
No size dummy[a]	0.09			
	(0.26)			
(1-nosize)*Log(init. scale)	0.11	***		
	(0.04)			
Log(init. scale)			-0.15	
			(0.11)	
Constant	1.48	***	1.36	***
	(0.32)		(0.48)	
N	76		56	
No. of firms	76		56	
Adj. R^2	0.49		0.54	
Encryption market dummy	Y		Y	
Entry cohort dummies (2)	Y		Y	

Notes: ***Significant at 1%. ** Significant at 5%. * Significant at 10%. [a] In spec. 1 since, 12 startups do not report their initial scale we use a no size dummy variable.

B. Results excluding VC funded firms:

A concern is whether our results, especially those that relate to failures and cash-outs are predominantly driven by the existence of VC funded firms in our sample. VC funded startups may have shorter time spans to evaluate a business opportunity and hence may be more likely to fail or cash-out earlier than other startups. Although we have attempted to control for VC funded firms using a VC dummy, VC dummy could also possibly be endogenous to performance measures such as cash-outs or even failures. In order to address this concern, we replicate our results that relate to cash-outs and failures using a sample of non-VC funded firms. This analysis is thus restricted to a sample that includes only 188 firms. We replicate table 5, using a sample of non-VC funded firms in table 11.

The results shown in table 11 are qualitatively similar to main principal results shown in table 6. Once again, firms started up by entrepreneurs with high opportunity costs not only have higher failure hazards but they have higher cash-out rates as well. An additional previous job is likely to increase the hazard of failure by about 18%. Moreover a standard deviation increase in the amount of work experience of the main founder is also likely to increase the hazard of cashing out by 26%. Our results with regard to initial scale are also qualitatively similar. While, a higher initial scale increases survival it also appears to increase cash-outs. Overall, these results are consistent with our principal results discussed earlier.

Table 11 –Competing hazard regressions of failure or cash-out using a sample of non-VC funded firms (standard errors in parentheses)[a]

	Failure		Cash-out	
Log(1+ prev. jobs)	0.50	***	0.72	**
	(0.15)		(0.24)	
Log (1+ patents)	-0.21	**	0.59	**
	(0.11)		(0.23)	
Log(1+parents TM)	-0.12	*	0.07	
	(0.06)		(0.06)	
Log (init. scale)	-0.09	***	0.64	***
	(0.01)		(0.12)	
Related startups dummy	0.37	***	0.57	***
	(0.11)		(0.21)	
Unrelated startups dummy	-0.01		-0.06	
	(0.22)		(0.20)	
Serial dummy	0.79	***	1.33	*
	(0.18)		(0.82)	
ISM tenure	-0.03	*	0.10	*
	(0.02)		(0.06)	

ISM tenure^2	0.01		-0.01	*
	(0.01)		(0.00)	
Industry age	-0.29	**	-0.26	**
	(0.15)		(0.12)	
Industry age^2	-0.02	***	0.01	**
	(0.00)		(0.00)	
Constant	-3.46	***	-3.12	***
	(0.23)		(0.44)	
N	1087			
No. of firms	151			
LL	-272.39			
Location parameter 1	-0.03, 0.07			
Location parameter 2	-0.11, 0.21			
Variance	0.45, 0.68			
Covariance	-0.07			
Probabilities	0.24, 0.76			
Submarket dummies(7)	Y			
Startup type dummies(3)	Y			

Notes: ***Significant at 1%. ** Significant at 5%. * Significant at 10%. [a] Standard errors cluster corrected by firm. The unit of observation is firm, year.

6 Discussion

In this paper we examined how opportunity costs of entrepreneurship influences subsequent performance. While the literature has mainly considered how opportunity costs of entrepreneurship influences selection into entrepreneurship, prior research to our knowledge has not considered this question. This paper hence adds to our understanding of how opportunity costs of entrepreneurship influences the tenure of entrepreneurship.

Our empirical results show that opportunity costs of entrepreneurship influences burn rates, cash-outs and failures. Entrepreneurs with high opportunity cost of entrepreneurship are likely to burn more cash. They are more likely to fail as well as cash out. Moreover such entrepreneurs are likely to have shorter tenures in the industry: not only are they likely to fail sooner they are also likely to cash-out sooner as well.

Further high opportunity cost entrepreneurs have higher threshold profits (minimum profit to enter profitably) because of which, high opportunity cost entrepreneurs end up entering the industry with better quality ideas. Better quality ideas on an average, results in longer survival and higher cash-out rates. With initial scale being a proxy for the inherent quality of the idea, entrepreneurs with high opportunity costs are likely to enter on a larger scale. Initial scale is also associated with lower failure hazards and higher cash-out hazards. These results support some of the previous findings in the literature that "better" startups enter on a larger scale and also performing better subsequently (Evans 1987a and 1987b, Dunne et al. 1988 and 1989, Philips and Kirchhof 1989, Audretsch 1991, Mata and Portugal 1994, Audretsch and Mahmood 1994 and 1995, Mata et al. 1995, Audretsch 1995b, Cabral and Mata 2003).

Our results also highlight some of the problems that bedevil using survival as a measure of performance. For one, our results show that differences in rates of survival, not only capture relative differences in performance, but preferences to linger on as entrepreneurs. Our also results show that a key factor that influences the preference to stay on, is the opportunity cost of entrepreneurs, of pursuing entrepreneurial activity.

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Appendix 1 – alternate model

We consider a three period model in which firms enter the industry in period 1. At the time of entry in period 1, firms are uncertain of their costs and hence profitability of the entrepreneurial venture. However firms share similar beliefs so that the expected profits of the venture, before opportunity costs do not vary between firms. At the time of entry, the entrant gets a private signal, that is only know to the entrepreneur, of viability of the venture in period 2. The signal is the payoff realized by the firm in period 2. The precision of the signal depends on the amount of investment, made by the entrant at the time of entry. Upon receiving the signal, entrants decide whether to stay on or quit. The opportunity costs of entrepreneurship determine the amount invested in the signal at the time of entry, as well the decision to stay on or quit in period 2. If the entrant decides to stay on past the period 2, the final payoffs are realized in period 3, and the venture can "fail" or "succeed" in period 3. Cash-out, occurs only in the event of two consecutive years of high profitability.

Notation and assumptions:

Entrepreneurs are heterogeneous in their opportunity costs, denoted by α, which is bounded between 0 and α_{max}. There are broadly two types of entrepreneurs – "Executives", or E type entrepreneurs are those that have high opportunity costs, and "Rookies" or R type entrepreneurs that have low opportunity costs. The exact conditions to derive the bound of α that divides entrepreneurs into E and R type are shown later.

Entrepreneurial opportunities are inherently uncertain and entrepreneurs share the same ex-ante beliefs about the nature of the opportunity. An entrepreneurial opportunity can either be blockbuster (B) an Average (A). A B type opportunity, has the potential to yield windfall profits in the future while an A type opportunity is one that at best yields normal profits. There is an ex ante probability P_B that an opportunity is blockbuster.

Entrepreneurs are uncertain about their costs and hence the outputs that they can produce and sell upon entering the industry. In period 1, entrepreneurs can choose to invest in acquiring diagnostic information, which costs z. The investment in diagnostic information provides a more precise signal of the viability of the idea. In particular, z reduces the probability of receiving a “false positive” signal. The signal is the payoff in period 2. The signal can either be a high (H type), or low (L type). Let Pr(H|B) = m and Pr(H|A) = x(z). Pr(L|B) is just 1-m while Pr(L|A) is 1-x(z). Notice that a higher z decreases the probability of false positives and hence increases the precision of the signal. We make two further assumptions: first, we assume that x, increasing and concave in z; second we assume that the probability of a true positive is weakly greater than the probability of a false positive or $m \geq x(0)$. This condition ensures that the expected profit of a venture is weakly increasing in P_B. Finally we also assume that 0<m<1.

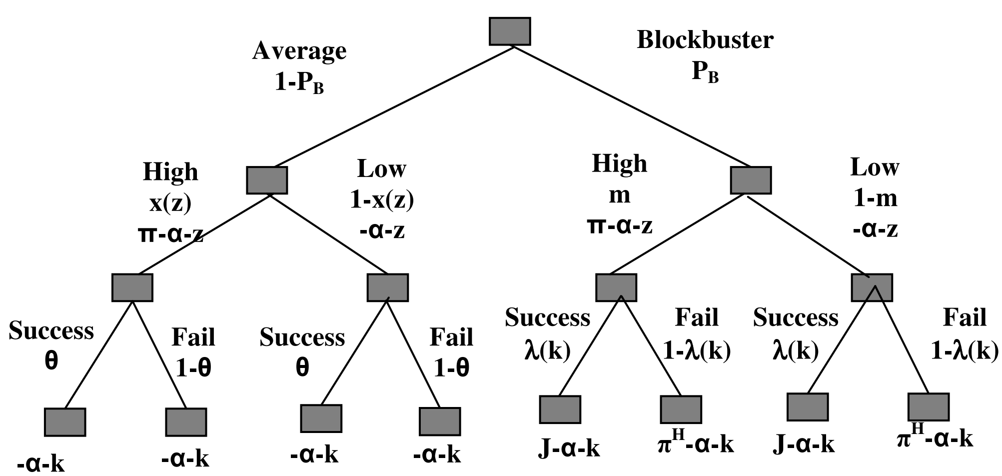


Figure 1 – Probabilities and payoffs

As explained earlier, the signal is the payoff realized by the firm in period 2. If the signal is of type H, the payoff in period 2 is π-α-z>0 and if the signal is of type L, the payoff in period 2 is just by -α-z.

Upon receiving the signal, entrepreneurs decide whether to stay on or quit beyond period 2. E type entrepreneurs because of having high opportunity costs are assumed to not find it worthwhile to continue if they do not receive a H type signal. Since R type entrepreneurs have low opportunity costs they do not quit in period 2 at all, no matter which type of signals they receive during that period.

Should the entrepreneur choose to stay on the venture could either "succeed" (S) or "fail" (F) in period 3. During this period, entrepreneurs have to decide on how much to invest on scaling up the venture, given by k. We assume that the probability of success is increasing and concave in k only if the opportunity was a B type opportunity. Stated otherwise, the scale up investment has no effect on probability of success of an A type opportunity. Let $Pr(S| . , B) = \lambda(k)$, $Pr(F| . , B) = 1- \lambda(k)$, $Pr(S|. , A) = \theta$ and $Pr(F| . , A) = 1-\theta$. We assume that λ is increasing and concave in k.

The payoffs in period 3 not only depend on whether the venture is a success in period 3, but also on the underlying nature of the opportunity. The type of signal in period 2 however does not affect the payoffs in period 3. The payoffs in period 3 are as follows. If the idea was of type A, the success or failure yields a payoff of $-\alpha$-k. However if the idea was of type B, success yields a windfall profit of payoff of $J-\alpha-k>0$, while failure yields of $\pi^H-\alpha-k>0$. These payoffs are assumed to be positive for all values of α and moreover $J> \pi^H >0$.

We first derive the bounds of α for the different entrepreneur types. Since E type entrepreneurs quit when they do not receive a positive signal, the expected profits to an E type entrepreneur is given by

$$V_E = mP_B\pi+(1-P_B)x(z)\pi-\alpha-z+mP_B(\lambda(J-\pi^H)+ \pi^H-\alpha-k)+x(z)(1-P_B)(-\alpha-k) \qquad (1)$$

Since R type entrepreneurs do not quit at all in period 1, the expected payoff from entrepreneurship for a R type entrepreneur is given by

$$V_R = mP_B\pi+(1-P_B)x(z)\pi-\alpha-z+mP_B(\lambda(J-\pi^H)+\pi^H)-\alpha-k \qquad (2)$$

There exists an α^* such that, $V_E=V_P$ (proof below). All entrepreneurs with $0\leq\alpha\leq\alpha^*$ are R type entrepreneurs, and entrepreneurs with $\alpha^*\leq\alpha\leq\alpha_{max}$ are E type entrepreneurs.

Entrepreneurs choose z optimally, with the optimal amount of investment in acquiring information given by z_E^* and z_R^* being the optimal investments for E and R type entrepreneurs respectively. z_E^*, is increasing in α, while $z_R^*=0$ and does not depend on α (proof below).

Entrepreneurs, tradeoff between the cost of acquiring information with the benefit of being able to averting future losses which is increasing in z. Since z decreases false positives, an increase in z enables entrepreneurs to avoid future losses due to false information. The model thus predicts entrepreneurs that have higher opportunity costs are more likely to invest in diagnostic information to find out the viability of the venture. Given higher opportunity costs, staying on is relatively more costly for a higher opportunity cost entrepreneurs. Hence entrepreneurs with higher opportunity costs have greater incentives to find out whether the venture is viable or not early. However R type entrepreneurs will not find it optimal to invest in diagnostic information since it has no value – the information does not change the action of R type entrepreneurs.

Result 1: z is increasing in α for E type entrepreneurs; *for R type entrepreneurs* $z_R^*=0$.

<u>Scale up investment:</u>

In period 3 entrepreneurs decide on the optimal amount of scale up investment k. Since E type entrepreneurs quit in period 2 if they do not receive a H type signal, E type entrepreneurs choose k to maximize Pr(A|H)($\theta\pi^H$-α-k)+Pr(B|H)(λ(J-π^H)+ π^H- α-k) ≡V_2^E. Using Bayes rule, V_2^E is given by

$$V_2^E = \frac{1}{mP_B + x(z_E^*)(1-P_B)}\left(mP_B(\lambda(k)(J-\pi^H)+\pi^H-\alpha-k)+x(z_E^*)(1-P_B)(-\alpha-k)\right) \quad (3)$$

Since P type entrepreneurs do not exit in period 2, R type entrepreneurs choose k by maximizing V_2^E + Pr(A|L)($\theta\pi^H$-α-k)+Pr(B|L)(λ(J-π^H)+ π^H-α-k)≡V_2^R. Once again using Bayes rule, V_2^P is given by

$$V_2^R = V_2^E + \frac{1}{(1-m)P_B + (1-x(z_R^*))(1-P_B)}\left((1-m)P_B(\lambda(k)(J-\pi^H)+\pi^H-\alpha-k)+(1-P_B)(1-x(z_R^*))(-\alpha-k)\right) \quad (4)$$

Let the optimal amount of scale up investment be $k_E^*$and k_R^* for E and R type entrepreneurs respectively. While k_R^*>0 and independent of α, the scale up investment of that of E type entrepreneurs, k_E^* increasing in α (proofs below). The model thus predicts entrepreneurs that have higher opportunity costs are likely to invest more in scaling up the venture. Since entrepreneurs with higher opportunity costs, are likely to invest more in acquiring diagnostic information, they are more likely to get a more precise signal of the viability of the venture. A precise signal in effect increases the marginal benefit of the scale up investment. Thus, entrepreneurs with higher opportunity costs are thus also more likely to invest higher in scaling up the venture.

Lemma: k is increasing in α for E type entrepreneurs; *for R type entrepreneurs the optimal scale up investment k_R^*>0, but is independent of α.*

<u>Probability of failure:</u>

We now compute the probability of failure. By construction E type entrepreneurs have a higher probability of failure in period 2 (they stay on beyond period 2 only if they receive a H type signal). In period 3, however, both E entrepreneurs stay on only if they can cash out. Thus the average probability of failure for E type entrepreneurs is just $1\text{-}mP_B \equiv \Phi_{E.}$ The average probability of failure of R type entrepreneurs however is just $1\text{-}P_B \equiv \Phi_R$

Result 2: E type entrepreneurs have the higher average probability of failure relative to R type entrepreneurs $\Phi_E > \Phi_R$.

<u>Cash-outs:</u>

Since cash out by construction can occur when the firm makes high profits in both periods 2 and 3, the probability of cash-out for all entrepreneurs is just $\lambda P_B m$. Since k is independent of α for R type entrepreneurs, the probability of cashing out for E type entrepreneurs is independent of α. However for E type entrepreneurs the probability of cashing out is increasing in α.

Result 3: The probability of cash out is increasing in α*. Entrepreneurs with higher opportunity costs have a higher probability of cashing out.*

While this model is adequate to generate predictions with regard to initial investments, probability of cash-outs and failures, it clearly this model is inadequate to generate predictions on how sooner the entrepreneur would cash-out or fail, as a function of opportunity costs of entrepreneurship. Moreover, the model assumes that the signal that the entrepreneur gets is private, upon which, she decides on the amount of scale up investment. However our data does not mandate that the signal should be private. Further empirically, we have no practical way to measure scale up investment. Nonetheless, this model does provide the intuition that entrepreneurs that have high opportunity costs are more impatient and that this should result in higher failure and cash-out rates.

Proofs of results:

1. We first show that ∃ a z_E^* that maximizes V_E and that , $z_R^*=0$.

   Recall, $V_E = mP_B\pi+(1-P_B)x(z)\pi-\alpha-z+mP_B(\lambda(J-\pi^H)+\pi^H-\alpha-k)+x(z)(1-P_B)(-\alpha-k)$

   $$\frac{\partial V_E}{\partial z} = (1-P_B)\frac{\partial x}{\partial z}(\pi-\alpha-k) = 1$$

   $$\frac{\partial^2 V_E}{\partial z^2} = \frac{\partial^2 x}{\partial z^2}(1-P_B)(\pi-\alpha-k) < 0$$

   Recall, that $V_R= mP_B\pi+(1-P_B)x(z)\pi-\alpha-z+mP_B(\lambda(J-\pi^H)+\pi^H)-\alpha-k$

   $$\frac{\partial V_R}{\partial z} = (1-P_B)\frac{\partial x}{\partial z}\pi - 1 < 0 .$$

   Thus $z_R^*=0$

2. z_E^* is increasing in α.

   $$\frac{\partial^2 V_E}{\partial z \partial \alpha} = -(1-P_B)\frac{\partial x}{\partial z} > 0$$

   $$\frac{dz_E^*}{d\alpha} = -\frac{\frac{\partial^2 V_E}{\partial z \partial \alpha}}{\frac{\partial^2 V_E}{\partial z^2}} > 0$$

   However z_R^* is independent of α and is 0.

3. We now show that ∃ an α^* s.t $V_E= V_R$

   First V_E is decreasing and concave in α.

   $$\frac{\partial V_E}{\partial \alpha} = \frac{\partial z}{\partial \alpha}\left(\frac{\partial x}{\partial z}\big((1-P_B)(\pi-\alpha-k)-1\big)\right) - mP_B - 1 - x(z)(1-P_B)$$

   Since E type entrepreneurs choose z_E^* optimally,

   $$\frac{\partial V_E}{\partial \alpha} = -mP_B - 1 - x(z)(1-P_B) < 0$$

   $$\frac{\partial^2 V_E}{\partial \alpha^2} = -\frac{\partial x}{\partial z}\frac{\partial z}{\partial \alpha}(1-P_B) > 0$$

   Second, V_R^* is decreasing linearly in α.

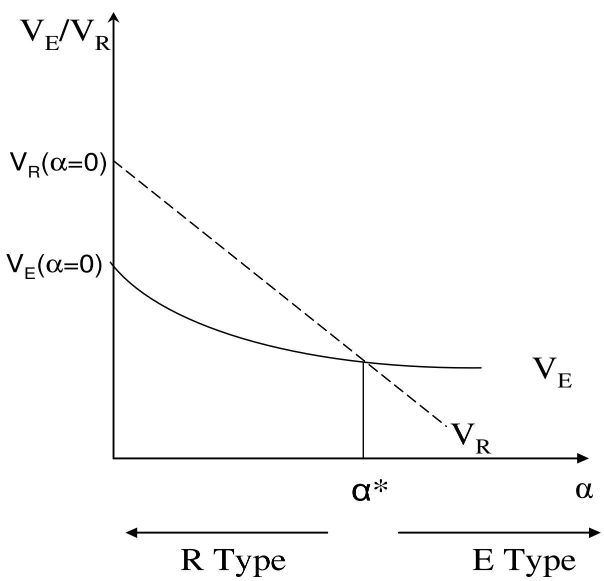
   $$\frac{\partial V_R}{\partial \alpha} = (1-P_B)\frac{\partial z}{\partial \alpha}\frac{\partial x}{\partial z}\pi - 1 - 1$$

Using the FOC, $\frac{\partial V_R}{\partial \alpha} = -1$

Third when α=0, $V_E < V_R$

When α=0, since 0<m<1

$V_E(\alpha=0) = mP_B\pi+(1-P_B)x(z(0))\pi-z(0)+ mP_B(\lambda J+(1-\lambda)\pi^H-k)) < V_R(\alpha=0)= mP_B\pi+(1-P_B)x(0)\pi+mP_B(\lambda J+(1-\lambda)\pi^H))-k$



4. $\exists$ a k_E^* that maximizes V_2^E and a k_R^* that maximizes V_2^R

Recall, $V_2^E = \frac{mP_B(\lambda(k)(J-\pi^H)+\pi^H-\alpha-k)+x(z_E^*)(1-P_B)(-\alpha-k)}{mP_B+x(z_E^*)(1-P_B)}$

$$\frac{\partial V_2^E}{\partial k} = \frac{1}{mP_B+x(z_E^*)(1-P_B)}\left(mP_B\left(\frac{\partial \lambda}{\partial k}(J-\pi^H)-1\right)-(1-P_B)x(z_E^*)\right)=0$$

$$\frac{\partial^2 V_2^E}{\partial k^2} = \frac{1}{mP_B+x(z_E^*)(1-P_B)}\left(mP_B\frac{\partial^2 \lambda}{\partial k^2}(J-\pi^H)\right)<0$$

Similarly, $V_2^R = V_2^E + \frac{(1-m)P_B(\lambda(J-\pi^H)+\pi^H-\alpha-k)+(1-P_B)(1-x(z_R^*))(-\alpha-k)}{(1-m)P_B+(1-x(z_R^*))(1-P_B)}$

$$\frac{\partial V_2^R}{\partial k} = \frac{\partial V_2^E}{\partial k} - 1 = 0$$

$$\frac{\partial^2 V_2^R}{\partial k^2} = \frac{\partial^2 V_2^E}{\partial k^2} < 0$$

5. k_E^* is increasing in α whereas k_R^* is independent of α.

$$\frac{dk_E^*}{d\alpha} = -\frac{\dfrac{\partial^2 V_2^E}{\partial k \partial \alpha}}{\dfrac{\partial^2 V_2^E}{\partial k^2}}. \text{ Since } \frac{\partial V_2^E}{\partial k \partial \alpha} = -mP_B(1-P_B)\frac{\partial x}{\partial z}\frac{\partial z}{\partial \alpha}\left(\frac{\partial \lambda}{\partial k}(J-\pi^H)\right) > 0,\ \frac{dk_E^*}{d\alpha} > 0$$

Similarly, $\frac{dk_R^*}{d\alpha} = -\frac{\frac{\partial^2 V_2^R}{\partial k \partial \alpha}}{\frac{\partial^2 V_2^R}{\partial k^2}}$. Since $\frac{\partial V_2^R}{\partial k \partial \alpha} = 0$, $\frac{dk_R^*}{d\alpha} = 0$

6. We now show that Pr(cash-out) is increasing in α for E type entrepreneurs whereas it is independent of α for R type entrepreneurs.

Recall, that the Pr(Cash-out) = $m\lambda P_B$

For E type entrepreneurs the probability of cash out is increasing in α

$$\frac{\partial \Pr(Cash-out)}{\partial \alpha} = m\frac{\partial \lambda}{\partial k_E^*}\frac{\partial k_E^*}{\partial \alpha}P_B > 0$$

For R type entrepreneurs the probability of cash out is independent of α

$$\frac{\partial \Pr(Cash-out)}{\partial \alpha} = m\frac{\partial \lambda}{\partial k_R^*}\frac{\partial k_R^*}{\partial \alpha}P_B = 0$$

7. We now show that that both P_B^* as well as P_B^{**} are increasing in α

Recall that P_B^* satisfies $mP_B^*\pi+(1-P_B^*)x(z)\pi-\alpha-z+mP_B^*(\lambda(J-\pi^H)+\pi^H-\alpha-k)+x(z)(1-P_B^*)(-\alpha-k)=0$

Totally differentiating this equation and using the FOC,

$$\frac{dP_B^*}{d\alpha} = \frac{1+x(z)(1-P_B^*)+mP_B^*}{(m-x(z_E^*))\pi + m(\lambda(J-\pi^H)+\pi^H-\alpha-k)} > 0$$

Similarly, recalling that

$mP_B^{**}\pi+(1-P_B^{**})x(z_R^*)\pi-\alpha-z_R^*+mP_B^{**}(\lambda(J-\pi^H)+\pi^H)-\alpha-k=0$

$$\frac{dP_B^{**}}{d\alpha} = \frac{1}{(m-x(z))\pi + m(\lambda(J-\pi^H)+\pi^H)} > 0$$

8. The average quality of opportunities is increasing in α for both E and R type entrepreneurs

For an E type entrepreneur, $E(P_B)=\frac{1}{1-F(P_B^*)}\int_{P_B^*}^{1} P_B dF$

$$\frac{\partial E(P_B)}{\partial \alpha}=\frac{\partial P_B^*}{\partial \alpha}\left(\frac{1}{1-F(P_B^*)}\right)\left[E(P_B)-P_B^*\right]>0$$

Similarly for an R type entrepreneur,

For an E type entrepreneur, $E(P_B)=\frac{1}{1-F(P_B^{**})}\int_{P_B^{**}}^{1} P_B dF$

$$\frac{\partial E(P_B)}{\partial \alpha}=\frac{\partial P_B^{**}}{\partial \alpha}\left(\frac{1}{1-F(P_B^{**})}\right)\left[E(P_B)-P_B^{**}\right]>0$$