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. Departing from the common practice of using survival as a measure of entrepreneurial performance, we model both failure and cash-out (liquidity event) as conditioned by the same underlying process. High-opportunity-cost entrepreneurs prefer a shorter time to success, even if this also implies failing more quickly, whereas entrepreneurs with fewer outside alternatives will choose less aggressive strategies, and, consequently, 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 more quickly but are also more likely to fail faster. Not only is survival a poor indicator of performance, but its use as one obscures the relationship between entrepreneurial characteristics, entrepreneurial strategies, and outcomes.

JEL Code: L250, L260

1 Introduction

Many entrepreneurs are very accomplished and have significant outside opportunities. These-high opportunity-cost entrepreneurs are interested in ventures with substantial "upside" potential. However, if this potential is not quickly realized, they would rather try their hand at something else (including,

[1] Corresponding author. This paper is based on a chapter of Nandkumar's 2008 PhD dissertation at the Heinz College, Carnegie Mellon University. The paper has improved in response to comments from anonymous reviewers of the *Journal*.

perhaps, a different startup) rather than linger on in a venture with modest prospects. They are also likely to be more aggressive in establishing the potential of the venture, accepting a higher risk of failure in doing so. This type of entrepreneurship motivates our paper.

We distinguish between two possible outcomes for a startup. It can fail (i.e., be dissolved) 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 from much of the literature by not treating survival as desirable in itself. Instead, survival merely keeps alive the option of trying for a cash-out. This option has an opportunity cost; thus, higher opportunity-cost entrepreneurs will adopt strategies that hasten a cash-out even if doing so entails a higher risk of failure.

We develop a simple model that formalizes this intuition. Each startup venture is characterized by a quality level, which determines its overall probability of success. In any period, the entrepreneur can take costly actions, hereafter called "investment", that increase the hazard of a cash-out. But striving for a cash-out also increases the hazard of failure: In trying to scale up quickly, the firm may run out of cash or hire the wrong people. Thus, in our model, increasing the investment increases how quickly the entrepreneur can cash out but also hastens the venture's failure. If the firm neither cashes out nor fails, it survives to try again. All else equal, an entrepreneur with a high opportunity cost will value the option embodied in survival less than an entrepreneur with low opportunity cost.[2] Our model also predicts that quality and opportunity cost interact in conditioning outcomes. The hazard of cash-out rises faster with opportunity cost in high-quality ventures, whereas failure rises more slowly. We test this intuition using a hand-collected dataset of startups (excluding diversifying firms) that entered the information security market (ISM) between 1989 and 2004.

This paper is organized as follows. The next 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 empirical analysis. Section 5 contains the results of the empirical analysis. We conclude in Section 6 with a discussion of the paper's implications and possible extensions.

2 Literature and background

2.1 Entrepreneurial opportunity cost and entry

Our paper draws on several streams of entrepreneurship research. The first stream examines the role of entrepreneurial opportunity cost. Much of the research has focused on how the decision of an entrepreneur to exploit an entrepreneurial opportunity depends on whether the expected profit is large

[2] 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.

enough to compensate for the opportunity cost (Shane and Venkataraman, 2000). Amit, Muller, and Cockburn (1995) show that potential entrepreneurs with high opportunity costs are less likely to select into entrepreneurship. Boden and Nucci (2000) find that startups in poor economic times have are more educated and experienced founders than those founded in better economic times. Fairlie and Chatterji (2008) find that high salaries in Silicon Valley during the boom in the 1990s lowered rates of firm formation relative to the period after the boom. We use this variation in the timing of entry as an alternative measure of opportunity cost in establishing the robustness of our empirical results.

2.2 Entrepreneurial opportunity cost and exit

While Knot and Posen (2005) note that exits from an industry may also result from excess entry, our work builds on the idea that higher opportunity costs of entrepreneurship will also trigger exits. Gimeno, Folta, Cooper, and Woo (1997) estimate a model of entrepreneurial performance where entrepreneurial human capital increases both the income and the threshold of acceptable profitability. Whereas in Gimeno et al. exit takes place when profits fall below threshold, in our model, entrepreneurial opportunity cost affects both entrepreneurial strategy and the threshold of acceptable performance. These differences also translate to differences in empirical specification. Gimeno et al. (1997) estimate a self-reported measure of performance, conditional on performance exceeding a threshold. In our model, failure and cash-out are two separate (but not independent) stochastic events, driven by the same strategic choices and conditioned by the quality of the venture.

Although survival has frequently been used as a measure of performance, recent scholarship has pointed out that it may be a very coarse measure. Headd (2003) uses census data to show that about a third of businesses that exited were in fact successful exits. Similarly, in a study of small businesses that were created between 1989 and 1992 and closed down between 1993 and 1996, Bates (2005) finds that some business owners described their firms as “successful” even though they were closing the business. Moreover, he finds that highly educated and skilled owners were more likely to move to other lines of work in successful closure situations.

Holmes and Schmitz (1990, 1995, and 1996) explore how failure, success, and survival are jointly determined. In their model, the match between the founder and the firm itself determines the longevity of the firm. When there is a good match with the firm, founders continue to manage their firms. However, when the match is poor, the firm is either shut down (when the firm is low quality) or sold (if the firm is high quality). We propose an alternative, albeit not mutually exclusive, mechanism that generates success and failures. In our case, the outcome in any period is a result of an “investment” decision made by the entrepreneur in each period. A key difference in implications is that whereas the Holmes and Schmitz (1990, 1995, and 1996) formulation would suggest that failing firms are poor-quality firms, and thus would grow less quickly, in our model, startups that fail quickly are also more likely to growing quickly.

Finally, our study also links to Åstebro and Winter (2001), who model successful exits, failure, and survival as multinomial outcomes. We too model these as multinomial outcomes that are generated by the same underlying decision-making process in every period. Åstebro and Winter (2001) distinguish a variety of ways in which financially distressed firms may exit, ranging from unfavorable acquisition to bankruptcy. We lump both modes of failure into one category (failure) in our empirical analysis, in part because the distinction is not salient in our framework, and in part because our sample is limited.

2.3 Founder experience, human capital, entry, and outcomes

The entrepreneurship literature finds that age and prior entrepreneurial experience are positively associated with selection into entrepreneurship (Levesque and Minniti, 2006; Parker, 2009). Older, more experienced, and better educated entrepreneurs may possess greater human capital and better social networks (Shane and Stuart, 2002). They may also be better able to evaluate and exploit new opportunities (Jovanovic, 1982).

The literature has also explored how human capital of the founder affects entrepreneurial performance. Firms started by more educated (Bates, 1990) or older entrepreneurs (Evans and Leighton, 1989) were more likely to survive longer. Several industry studies also find that pre-entry experience (related to entrepreneurial opportunity cost) is valuable and improves performance, although there is less clarity on which type of experience is most valuable. Much, though not all, of this literature also uses survival as a measure of performance.[3] By neglecting the potential for a quicker cash-out, this literature potentially misses an important aspect of the link between entrepreneurial experience and the performance, namely that pre-entry experience is also valuable in other pursuits.

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. In our baseline model, all else equal, higher quality ventures have lower hazards of failure and higher hazards for cash-out. For simplicity, we do not model entry into entrepreneurship, because it is very difficult to empirically identify the set of potential entrants. Instead, we treat venture quality and opportunity cost as two separate parameters that are known to the entrepreneur at the time of entry. In the empirical analysis, we independently control for venture quality to estimate how opportunity costs influence failure and cash-outs.

A different interpretation of pre-entry experience is that it provides the entrepreneur with better judgment and discernment, about the venture as well as about his or her own abilities. Thus, in the spirit of Jovanovic (1982), one might expect that an experienced founder is better able to decide when to push ahead and when to pull the plug. Consequently, pre-entry work experience would result in quicker

[3] See for instance, Klepper (2002) on automobiles, Thompson (2005) for shipbuilding, and Klepper and Sleeper (2005) for lasers.

success, but also quicker failure. This is another mechanism that is consistent with the broad empirical finding we report. However, insofar as work experience in IT confers greater judgment ability as compared to work experience in unrelated industries, we can empirically distinguish this explanation from the opportunity cost explanation, as we discuss in the robustness section.

2.4 Work experience, wealth, and risk-bearing

As shown below, in our model an increase in investment made by a startup implies higher probability of both success and failure, but leaves the expected outcome unchanged. In other words, entrepreneurs undertake "riskier" projects, *because they have higher opportunity-cost*.

However, there are other mechanisms linking experience with project risk which are unrelated to opportunity cost. For instance, Bhide (2003) argues that a spinoff from an existing firm is more likely to implement a riskier idea. A less risky idea would likely be implemented inside the parent firm itself, *if the parent is in a related industry*. Moreover, the more senior the employee, the riskier the idea he or she is likely to be able to implement internally. Thus, conditional on observing a startup, a more experienced founder is likely to be associated with a riskier project, but only for startups from the IT industry itself. For startups from unrelated industries, such as banking, experience should not be systematically related to failure and success. In the robustness section, we check whether the effect of work experience on success and failure systematically differs between IT and unrelated startups. As an additional robustness check, we directly control of risk using the coefficient of variation.

A different mechanism links experience with wealth. Entrepreneurs with more work experience could be less wealth constrained (e.g., Evans and Jovanovic, 1989). Insofar as wealth relaxes liquidity constraints, this should increase the likelihood of success but should correspondingly decrease failure, contrary to our empirical findings.

Greater wealth may also lead to more risk taking.[4] Lacking measures of wealth, we cannot conclusively distinguish this mechanism from the one based on opportunity cost. However, as noted, we also use other proxies for opportunity cost, including whether the entrepreneur has patents prior to entry (indicating the outside option) as well as the timing of the startup (which measures how plentiful outside employment opportunities are). We also separately control for whether the startup receives venture capital financing, and for serial entrepreneurship (which might also control for wealth effects).

2.5 Founding teams

Startups typically have multiple founders and differ in size and quality of the founding team. Prior work has found that firms with multiple owners survive longer (Cressy, 1996; Åstebro and Bernhardt, 2003).

[4] Evans and Jovanovic (1989) do not find any evidence that wealth is positively related to entrepreneurial ability (which they interpret as including the ability to bear risk), but Xu (1998) finds opposite results using later data. Cressy (2000) provides a model in which wealth decreases risk aversion, thereby explaining the relationship between wealth and selection into entrepreneurship.

We ignore the rich set of issues around the composition of the founding team and the potential differences in objectives among its members because there is relatively little settled theory on how founding teams condition the performance of a startup (Hsu and Marino, 2010) and focus on the link between opportunity cost of waiting and start-up strategy by controlling for the number of founders in our empirical analysis.

2.6 Investors

Investors may affect how aggressively the startup seeks to cash out. For instance, Goldfarb, Kirsch, and Miller (2007) find that firms following the rapid-growth strategy were more likely to be venture-funded but also had much higher failure rates. Goldfarb et al. (2007) interpret the choice of a rapid-growth strategy as a mistake, the outcome of a belief cascade among investors. Instead, our framework implies that such differences in strategy may reflect differences in entrepreneurial opportunity cost, not merely hubris; a higher risk of failure may be optimal for impatient entrepreneurs if it shortens the time to cash-out. In the empirical analysis, we explicitly control for VC financing. Our results also hold when we only analyze firms that are not VC funded.

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, will invest more resources in return for a quicker cash-out.

3.1 Setup

Let P, where $0 \leq P \leq 1$, 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 investment, the "burn rate", or the targeted level of growth of the venture. We require that $0<m<1$ to ensure that the probabilities are well defined.

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 entrepreneur 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 $(0\leq \beta \leq 1)$ is the discount factor.

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

Result 0: The probability of success is P and the probability of failure is 1-P.

Proof: The probability of success is simply $Pm((1-m) + (1-m)^2 + (1-m)^3 \ldots) = P$.

Let $c(m) \equiv m^2/2$.[5] The expected profit of an entrepreneur with opportunity cost of α 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

$$PJ - \beta V - m = 0 \qquad (2)$$

Rearranging, imposing $0<m<1$ and writing $A \equiv ((1-\beta(1-PJ))^2 + 2\beta^2\left(\alpha - \frac{P^2J^2}{2}\right)$, the first order condition implies that the optimal *m,* is

$$m^* = \left(1 - \frac{1}{\beta}\right) + \frac{A^{1/2}}{\beta}. \qquad (3)$$ [6]

Note that A is increasing in α, and m^* is increasing in A, so that m^* is increasing in α (all proofs are shown in appendix 1).

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

3.2 Opportunity costs and hazard of cash-out and failure

The hazard of cash-out – the probability that a firm cashes out in period t given that it survives until t – is $\Phi \equiv m^*P$. From Result 1, m^* increases with α. Therefore the hazard of a cash-out also increases 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 until t, is $\Omega \equiv m^*(1-P)$, which is increasing in m^*, so that the Result 1 implies that hazard of failure increases with α as well.

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

3.3 Quality of venture and hazard of cash-out

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 with *P*. Intuitively, a higher *P* raises the marginal product of *m* by increasing the probability of cash-out and lowering the probability of failure.

[5] The results hold as long a C(*m*) is convex in *m*.
[6] Note that since $0 \le m \le 1$, $A^{1/2}$ is bounded between 1-β and 1, because V>0.

Result 2: Higher quality ventures have higher m.

Since m^* is increasing in P, it follows that not only are higher quality ventures more likely to succeed, but they do so more quickly.

Prediction 3: Higher quality ventures have a higher hazard of cash-out.

3.4 Interactions between venture quality and opportunity cost

Thus far, the predictions of the model have been straightforward. Our prediction about the interaction between venture quality and entrepreneurial opportunity cost is less obvious. Formally, we show in appendix 1 that $\frac{\partial^2 \Phi}{\partial \alpha \partial P} > 0$. This implies that high-opportunity-cost entrepreneurs succeed more quickly 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 for a low-quality one.

The effect of venture quality on failure, however, is 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 m, higher quality also increases m, which increases the hazard of failure. We show in the appendix that for low values of P, the hazard of failure increases in P because the latter effect dominates. For high values of P, the former effect dominates.

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

3.5 Discussion and extensions: The model is stylized to focus on the role of entrepreneurial opportunity cost on measured rates of failure and success. The role of investment is simply to make the uncertainty resolve more quickly, without affecting the overall rates of success or failure. The model can easily be extended by allowing overall probabilities of success and failure to depend upon investment rates as well (extension shown in appendix 1.1). For instance, if one lets the hazard of success be Pm as before but that of failure be $(1-P)\delta(m)$, where $\delta(m)$ is an increasing function of m, the overall probability of success (not the hazard of cash-out) is 1/(1+B), where $B \equiv \frac{(1-P)\delta(m)}{Pm}$, which decreases with m if $\delta(m)$ is elastic with respect to m. The other results, namely that m increases with opportunity cost and the hazard of success and failure increases with opportunity cost, continue to hold.[7] In sum, the simplification that m only compresses the time required to resolve uncertainty, without affecting the overall likelihood of success or failure, does not affect the principal insights of the model.

4 Data and measures

Our sample consists of 286 ISM startups, followed from the time of entry until 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. While we believe that our theory is not specific to any particular industry, the information security is a high-tech sector where entrepreneurs can create ventures with significant upside potential, which is key to our theory. Some, but not all, startups are VC-funded, and some founders are from outside the IT industry, which provides useful variation. Given the recent origin of the industry, we are also able to acquire detailed information on founder backgrounds, and to get a comprehensive set of entrants into the industry. We augmented the dataset with information about the founders (for up to 4 founders of each startup) 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), the EDGAR database, and the Zephyr database. For firms with multiple founders, the founder with the most work experience was designated as the main founder and his or her characteristics were then used to characterize the startup.

<Table 1 here>

Cash-out and Failure:

Failure: We first identified whether a startup had exited using the CorpTech database.[8] We then identified a startup as having failed if it either went bankrupt or was acquired on unfavorable terms. An acquisition was classified as unfavorable using the following criteria: (i) for VC funded startups, if the transaction value (the value of the acquisition deal) was less than the total capital raised; (ii) if a startup was not VC funded and reported a loss in the year prior to the acquisition; (iii) if the startup is not VC-funded and we lack profitability data, if none of the founders of the focal startup joined the acquiring firm. We dropped 14 acquisitions for which the key data elements required to apply these criteria namely the transaction value of the acquisition, profit/loss in the year preceding acquisition, and the whereabouts of all the founders of the startup were untraceable.

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[7] However, the sign of the cross-partial of the hazard of failure with respect to opportunity cost and P is ambiguous.
[8] All firms that exited Corptech before 2004 were coded as exits (but not necessarily as failed). For firms that continued in Corptech after 2003, we searched archive.org to determine if they were still in business or not.

We identified the year of failure as the year in which the corporate web site was last available on www.archive.org, a site that contains historical archives of all Internet web sites. The year of failure in the case of distress sale was year of the sale.

Cash-outs: We define cash-out as a favorable acquisition (an acquisition of a VC-funded startup whose transaction value exceeded total capital raised, or an acquisition of a non-VC-funded startup that reported a profit in the year preceding acquisition, or, absent that data, acquisition of a non-VC-funded startup that resulted in at least one of the founders joining the acquiring firm) or an Initial Public Offering (IPO), whichever was earlier. We identified the date of acquisition using the Zephyr database. Table 1 summarizes our classification scheme for success and failures. As the table shows, there were 58 successes in all, of which 36 were IPOs and the remaining 22 were favorable acquisitions. There were 53 failures, of which 10 were bankruptcies or distress sales and 43 were unfavorable acquisitions.

Our results are robust to alternative ways of defining failure or cash-outs, such as retaining all acquisitions and (a) treating all acquisitions for which the press release accompanying the acquisition did not provide a transaction value as failure and all acquisitions for which the press release provided a transaction value, or (b) only treating bankruptcies as failure and IPOs as cash-outs.

Opportunity cost:

We develop several 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. Work experience is measured as the number of years from the year that the founder received his or her last academic degree until the year of founding of the focal startup. This measure assumes that greater work experience is associated with higher potential wage earnings.

Our second measure is the wage, in 2004 dollars, in the founder's industry and occupation in the year that the startup was established.[9] We obtained this variable by matching the prior job description and industry of every founder of the focal startup with the closest industry and job description match in the Bureau of Labor Statistics (BLS) Occupational Employment Statistics (OES) database for the year in which the focal startup was established. For firms with multiple founders, we take the maximum of the wages of all founders of the focal startup. The matching of industries, and of job descriptions, both require judgments, especially since job descriptions of founders (prior to the startup) were obtained from sources such as Linkedin.[10]

[9] Using the average experience and average wages yielded qualitatively similar results.

[10] We assigned the maximum wages in our dataset for founders that were entrepreneurs immediately prior to founding the focal ISM startup and minimum wage of the OES database where the founder had no experience.

We use another time-based measure of entrepreneurial opportunity costs, Internet bust years =1 if the focal firm was founded after 2000. Arguably, entrepreneurs would have low opportunity cost post-bubble, as employment opportunities in IT shrank (cf. Fairlie and Chatterji, 2008).

Insofar as opportunity cost depends also on innate qualities such as creativity and technical expertise, we control for the number of patents held by the main founder of the focal startup, weighted by the number of forward citations (founder patents, henceforth). This is a narrower measure of opportunity cost, measuring the technical creativity and expertise of the founder.[11]

Venture quality:

We use three measures of 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. For instance, Jovanovic'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. Empirical studies show that initial firm size is highly correlated with firm performance, albeit typically measured as survival (Evans, 1987a and 1987b; Dunne, Roberts, and Samuelson, 1988 and 1989; Phillips and Kirchhoff, 1989;; Audretsch and Mahmood, 1994 and 1995; Mata, Portugal, and Guimaraes, 1995; Cabral and Mata, 2003; Mata and Portugal, 1994; Agarwal and Audretsch, 2001).

We supplement initial scale with specific measures of the marketing capability and technical capability of the venture. We proxy for the marketing ability of startups by the number of IT trademarks of the previous employer of the founder (parent IT trademarks, henceforth) at the time of entry.[12] This measure is valid insofar as the founder "inherited" some of marketing ability from the earlier employer. In cases where the startup had multiple parents, we use numbers from the parent with the greatest number of IT trademarks. Hsu and Ziedonis (2008) argue that the number of patents of startups signals venture quality. Accordingly, we use the U.S. information security patents (U.S. patent technological class 705, subclass 50-79, 380, and 726) assigned to the startup at the time of formation as a measure of technical ability (security patents henceforth). As is customary, we weight each patent by forward citations, adjusting for year of grant.

Controls

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[11] Founder-patents may also measure firm quality, but since we also control for initial size (which the literature has shown is a very good measure of quality), founder-patent plausibly captures variations in opportunity cost.

[12] We searched the US PTO trademarks database (http://tess.uspto.gov) for trademark descriptions ("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").

<u>Market-segment fixed effects</u>: We use 7 market-segment fixed effects: encryption products, network security, authentication, firewalls, antivirus, spam control, and hardware, with consulting being the residual market segment.[13]

<u>Firm age</u>: 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 earliest. We use this measure to control for age dependence (Dunne et al., 1988; Evans, 1987a; Audretsch and Mahmood, 1995; Mata and Portugal, 1994). To allow for non-linearities, we also include the square term.

<u>Industry age</u>: It is plausible that firm survival may vary as the industry grows and matures. We hence control for this using industry age, which is simply the number of years from 1970.

<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, 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 (those with founders from universities, military or government). The left-out category is of the firms with founders with untraceable backgrounds and hackers.

<u>Source of capital</u>: In many of our specifications we also control for the source of capital of startups (as binary variables). 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.

<u>Number of founders</u>: In all our specifications we also control for the number of founders.

Table 2 summarizes the measures and provides descriptive statistics. Around a quarter of the startups in our sample fail; 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 just over a third of them received venture capital funding.

< Table 2 here>

5 Empirical analysis

<u>5.1 Non-parametric analysis</u>

Table 3 provides the share of cash-outs and failures by entrepreneurial opportunity cost and venture quality. Comparing columns *b* and *c* shows that higher opportunity cost increases the cash-out share (0.26 compared to 0.16) as well as share of failure (0.25 compared to 0.16 in columns *e* and *f* respectively). The differences in both cases are statistically significant. Further, higher venture quality increases the cash-out

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

share from 0.09 to 0.31 (Column *a*). Column *d* shows that venture quality decreases share of failure from 0.27 to 0.15. This suggests that our primary measure of venture quality, initial scale, is plausibly a good summary measure of the overall quality of the venture, which includes both the quality of the idea and 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 columns *b-c*, comparing row (1) with row (2), we see that for high-quality ventures the difference in cash-out probabilities is 0.15; the difference is 0.08 for low-quality ventures. Although statistically insignificant, the "difference-in-difference" is 0.07. The second prediction was that the share of failure should increase with opportunity cost more slowly for higher quality ventures. Comparing rows (1) and (2) in columns *e-f* shows that the difference in failure share is 0.04 for high-quality ventures and 0.14 for low-quality ventures. The difference-in-difference (-0.10) is negative, though not statistically significant.

<Table 3 here>

The results of this simple cross-tabulation are significant in that all the major predictions of our simple model are borne out here, including the predictions on the signs of the cross-partials. However, Table 3 shows shares rather than the per-period probabilities and thus does not control for the differences in firms' entry dates. 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 specification that jointly estimates the hazard of failure and cash-outs.

5.2 Parametric analysis

We estimate a competing hazard model in which there are two absorbing states: failure and cash-out. Following Boyd, Lankford, Loeb, and Wyckoff (2005), we implement a discrete time-hazard regressions specification also used in Martin and Mitchell (1998) and King and Tucci (2002).[14]

Our simple model implies a nested specification in which survival is decided first with probability (1- m_i) and, conditional upon survival, the ratio of cash-out and failures is $P_i/(1-P_i)$. A more general specification (see Section 3.5) would allow the probability of cash-out and failure to also depend upon *m*. 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-specific unobserved heterogeneity. The probability of failure is analogously specified. We assume that the unobserved heterogeneity is normally distributed with mean zero and variance σ.

[14] Continuous time specifications such as Cox proportional hazard yield qualitatively similar results.

We use 2117 observations, where the unit of observation is a firm-year from the year of entry until year of failure, cash-out, or 2004, whichever is earliest. In our baseline specification, we exclude observations relating to 23 firms[15] since data on founder characteristics or, less frequently, on initial scale, was missing. Including the dropped observations by assigning the sample minimum size of 2 employees to firms that do not report initial size as well as a minimum work experience value of 0 to firms whose founder does not report work experience leaves our results unchanged.

As in Table 3, the results of the baseline specification shown in Table 4 indicate that entrepreneurs with higher opportunity costs are more likely to fail. One-standard-deviation increase in experience increases the hazard of failure by about 28% and the hazard of cash-out by 22%. Similarly, security patents and parent IT trademarks increase the hazard of cash-out as well as the hazard of failure. Initial scale (our measure of quality), however, reduces failure – the estimated coefficient is negative and statistically significant – and increases success. Interestingly, having more founders increases the hazard of cash-out but decreases the hazard of failure, confirming Cressy (1996) and Åstebro and Bernhardt (2003). As further evidence, note that the coefficient Internet bust years implies that startups formed after the Internet era were less likely to cash out but also less likely to fail. 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.[16] Also consistent with our theory, serial entrepreneurs have a higher hazard of cash-outs as well as failures.

<Table 4 here>

Specification 2 includes controls for whether the startup received VC funding or corporate VC. Notice that by controlling for venture funding we are potentially making it harder to find an effect of opportunity cost since venture capitalists tend to push their portfolio companies to adopt aggressive growth strategies (e.g., Goldfarb et al., 2007). However, even after controlling for differences in funding sources, the coefficient of work experience is positive and significant in both cash-out and failure equations. Also, in unreported estimations, we find that our results are unchanged if we only focus on ventures that are not VC funded. This indicates that our results on the effects of opportunity cost are not driven by differences in funding sources.

Specification 3 of Table 4 shows results when we include dropped observations with missing data by assigning sample minimum values for initial scale and work experience. The inclusion of the 23 dropped observations does not change our results. Our results are also qualitatively similar when we allow

[15] Of 272 firms for which we could trace outcomes, 12 startups not report initial size although we were able to trace founder histories for these startups. For 11 startups neither founder histories nor initial sizes are available.

[16] After 2000, the drying up of the IPO market likely reduced cash-outs. However, the stock market problems should also have increased failure (rather than decreasing 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 unobserved firm-specific intercept to have an arbitrary three-point discrete distribution, as shown in specification 4 of Table 4. Estimating the unobserved heterogeneity non-parametrically, such as by allowing the u_f (and u_c) to have an arbitrary distribution with three points of support, yields very similar results, as shown in Table 4, column 4. Unreported specifications where the distribution of unobserved heterogeneity varies across submarkets (e.g., between those based on encryption technology and others) yields qualitatively similar results. Ignoring unobserved heterogeneity altogether does not significantly alter our results either.[17]

We next test predictions that cash-outs should increase more rapidly with opportunity cost for high-quality ventures, but failures should increase more slowly. Table 5 shows first the results when we estimate two separate equations, one each for firms with above- and below-average initial scale. When the initial entry scale is low, a one-standard-deviation increase in work experience increases the hazard of failure by 41%, whereas the same change increases failure by only 8% for high-quality ventures. The difference between "high" and "low" is 0.33 (std. err - 0.12; p-value 0.01).[18] A one-standard-deviation increase in work experience increases cash-out hazard by 9% for low-quality ventures and 1.46 times for high-quality ventures. The difference between "high" and "low" is 1.37 and is both large and statistically significant (std. err = 0.17; p-value = 0.00).

<Table 5 here>

In specification 2 of Table 5, we simply interact work experience and scale (instead of splitting the sample) and get similar results. In figure 1A and 1B, we interpret the interaction terms graphically by comparing the hazards of failure and cash-outs at different points in the work experience distribution. Figure 1A examines the hazard of failure. For a founder with initial size at the 10th percentile, increasing work experience from the 50th to the 75th percentile increases the hazard of failure (relative to the baseline) by about 106%. However, for a startup of 50th percentile initial size, moving from 50th percentile work experience to 75th percentile increases the hazard of failure by only 10%. Thus the effect of work experience on the hazard of failure increases more rapidly for low-quality startups. This result lends support to prediction 6.

Figure 1B shows that the effect of experience on the hazard of success is larger for a startup of higher quality relative to a startup with lower quality. For a startup of 10th percentile initial size, increasing work experience from 50th to 75th percentile increases the hazard of success by only about 35%. In contrast, for a startup of 50th percentile initial size, moving from 50th percentile work experience to the 75th percentile increases hazard of success by 101%, consistent with prediction 4.

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[17] Unreported specifications where we additionally control for education of the founders (e.g., whether the founder had a PhD, or an MS in Computer Science or Electrical Engineering) yield very similar results.
[18] The standard errors for comparing coefficients in Table 5 are obtained by bootstrapping, based on 50 iterations.

<Figures 1A and 1B here>

5.3 Robustness checks

5.3.1 Alternative measure of opportunity cost

As discussed earlier, we explore the robustness of our results to alternative measures for entrepreneurial opportunity cost. Recall that firms founded immediately after the Internet bubble (with fewer employment opportunities for IT workers) show outcome patterns consistent with lower opportunity cost, namely lower rates of failure and cash-out. Here we explore two other measures. We replicate our principal results using Bureau of Labor Statistics wages based on the industry and occupation of the founder as a measure of opportunity cost. As Table 6, specification 1 shows, BLS wages of the entrepreneur are associated with higher cash-out but also higher failure hazards. In specification 2, we use founder patents as a measure of opportunity cost. Researchers who produce more patents likely enjoy a greater demand for their services, and thus have higher opportunity costs. We find that our principal results are unchanged to the use of founder patents instead of work experience as a measure of opportunity costs.

<Table 6 here>

5.3.2 Alternative interpretations of work-experience

Risk taking and work experience

As noted in Section 2, entrepreneur opportunity cost may be correlated with project risk (and hence may condition hazards of failure and cash-out) without being causally linked. Many of the ideas that are exploited by startups are those that the employer does not want to pursue. It is plausible that the more senior the employee, the riskier the idea he or she is likely to be able to implement internally (Bhide, 2003). Thus, conditional on observing a startup, a more experienced founder is likely to be associated with a riskier project. However, note that if the employer is in an unrelated industry (such as banking or government), the employer would not pursue even low-risk ideas. In other words, experience should be correlated with risk in founders employed in IT firms but not from others. If project risk was driving our results, we should find a systematic difference between founders employed in IT firms and those in other firms.

A similar prediction emerges from the interpretation of work experience as endowing superior judgment ability on the entrepreneur, enabling the entrepreneur to pull out of an unpromising venture more quickly, or push harder on a promising venture. Once again, it is likely that prior experience in the IT sector should be more useful as compared to experience in unrelated industries. Conversely, if the relationship is due to high-opportunity-cost entrepreneurs being more impatient, there should not be any systematic differences across IT and non-IT founders. Note that we control for technical ability using security patents, to minimize the probability of confounding work experience with technical ability.

In specification 1 of Table 7, we divide our sample in two – related startups (founder from IT firm) and unrelated startups – and estimate the competing hazard specification separately. Table 7 shows that there is virtually no difference in the results of the two sub-samples, indicating that it is unlikely that the results are confounded by unobserved differences across entrepreneurs in ability to judge.

In specification 2 of Table 7, we include a measure of riskiness of a venture, the coefficient of variation (CV henceforth) calculated as standard deviation over the three-year mean of employee size[19]) as an additional control. Specification 2 of Table 7 shows that despite the inclusion of CV as a control, our results are qualitatively similar to those discussed earlier. A one-standard-deviation increase in work experience is associated with about a 27% increase in the hazard of failure, and a similar increase is associated with about a 28% increase in the hazard of cash-out. Also as expected, riskier ventures (projects with higher three-year CV) are more likely to cash-out as well as fail earlier. In unreported estimates, we find that this pattern also holds with our other measures of opportunity cost, wages and founder-patents.

Since neither measures of risk-preferences nor measures of wealth are available, we cannot conclusively distinguish our explanation from those based on ability or willingness to bear risk (unrelated to entrepreneurial opportunity cost). However, as noted, other proxies for opportunity also cost yield qualitatively similar results, and direct controls for riskiness, leave the coefficient of opportunity cost unaffected.

<Table 7 here>

5.3.4 Fit, ability to discern, and work experience

As noted in Section 2, our primary measure of opportunity cost – namely experience – may also be correlated with “fit” between the entrepreneur and the firm, as suggested by Holmes and Schmitz (1996). Our primary measure of opportunity cost, work experience, could be correlated with "fit".

In our model, high-opportunity-cost entrepreneurs invest aggressively in search of a quick cash-out. By contrast, a poor fit between the entrepreneur and the firm should be reflected in lower growth, eventuating either in a sell-off or in a bankruptcy. Therefore, insofar as aggressive investment is reflected in growth in the number of employees, we can empirically distinguish between these two mechanisms. In specification 3 of Table 7, we replicate specification 1 of Table 3, but include the growth in the number of employees (growth, henceforth; calculated as difference between current and previous year employees

[19] We are grateful to an anonymous reviewer for the suggestion. For 5 firms we are unable to calculate CV due to missing sizes for one or more years. This leaves us with 244 firms and 2074 observations in total.

divided by previous year employees) as an additional independent variable.[20] The results show that including growth as an additional independent variable diminishes the coefficient of work experience, while the coefficient of growth is positive and statistically significant in both success and failure equations. A one-standard-deviation increase in work experience now only accounts for about a 5% increase in the hazard of failure and a 7% increase in the hazard of success as opposed to 28% and 22% as reported in Table 4. Moreover, growth is positive and statistically significant in both the equations.

Though one should view these results with caution since growth in employment and the coefficient of variation are themselves related to a number of unobserved aspects of firm quality and strategy, they are significant on three counts: first, our results indicate that faster growth is associated with failure, as predicted by our model but contrary to the mechanism envisaged by Holmes and Schmitz (1996), wherein slow or negative growth reflects a poor fit between the entrepreneur and the venture, rather than a more conservative entrepreneurial strategy. Second, these results show that that work experience is picking up differences in opportunity cost rather than differences in the ability to quickly discern the inherent quality of the venture. If our results were an artifact of differences in ability to discern, growth should be negatively related to failure and positively related to success, contrary to our results. Third, controlling for riskiness directly, using the coefficient of variation does not materially change our findings, indicating that although failure and success are related to risk, our measure of opportunity cost is not picking up the effect of risk.

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 operating on a large scale. In these cases, survival of the startup is not the objective.

It is well known that the use of survival as a measure of performance, common in research in this field, is problematic. 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

[20] For 5 firms we are unable to calculate employee growth for every year. Moreover since we use growth we also lose one year for every firm. This leaves us with 1830 observations for this specification.

such costs raise the threshold for staying on, they also – as we show – affect the strategies of entrepreneurs, which in turn affect measured rates of survival and 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 and failures. The broader intuition is that 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.

Our empirical results show that opportunity costs of entrepreneurship influence both successes 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. 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.

Although we have tried hard to probe the robustness of our findings in a variety of ways, we recognize the many caveats and qualifications that one must attach to the findings of a simple model tested with data from a single industry. Caveats notwithstanding, our principal contribution is to show that entrepreneurial opportunity cost is important for understanding entrepreneurial strategy, and hence also entrepreneurial outcomes, especially in contexts where entrepreneurial ventures have high upside-potential, such as in innovation-based ventures.

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Table 1 – Classification of outcomes

Description	How defined	#	#
Total surviving startups (Neither success nor failure) (A)			161
Bankruptcy or asset sale (B)	Press report clearly said that the acquisition was distress	10	
Unfavorable acquisitions (C)	<u>VC-funded firms</u> if transaction value was less than total capital raised (available for all VC-funded startups and 11 in all) <u>Non-VC-funded firms</u> (a) if the focal startup reported a loss in the year preceding acquisition (17 in all) (b) if information in (a) was unavailable, if none of the founders joined the acquiring firm (15 in all)	43	
Favorable acquisitions (D)	<u>VC-funded firms</u> if transaction value was higher than or equal to the total capital raised (available for all VC-funded startups and 17 in all) <u>Non-VC-funded firms</u> (a) if the focal startup reported a profit in the year preceding acquisition (2 in all) (b) if information in (a) was unavailable if one or more founders joined the acquiring firm (3 in all)	22	
Total acquisitions (E=C+D)		65	
IPOs (F)	Corptech/VX database	36	
Total failures G=B+C			*53*
Total success H=D+F			*58*
Acquisitions that could not be classified as cash-outs or failure (not used in empirical analysis)			**14**
Total startups I=A+G+H			**286**

Table 2: Description of measures used

Variable	Description	level	N	Mean	Std. Dev
Failure	=1 if the startup went into a distress sale or went out of business completely.	Firm	272[a]	0.20	
Cash-out	=1 if the startup was acquired on favorable terms or had an IPO.	Firm	272[a]	0.21	
Work experience	Log(1+ # years of work experience) of the main founder. Measure of opportunity cost.	Firm	261[b]	1.27	1.63
Founder patents	Log(1+ # patents) held by the founder that had the most patents among all founders of the focal startup. Measure of opportunity cost.	Firm	261	0.32 0.32	0.72 0.72
Wages	Log(1+wages) of the founder of the startup. Max. of the wages if multiple founders. This is yet another proxy for opportunity cost.	Firm	261	11.24	5.12
Initial scale	Log of (1+ # employees of the startup at the time of entry). This is our proxy for the quality of the startup.	Firm	249[c]	3.59	1.41
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
Founder patents	Log (1+ # patents held by the main founder of the focal startup.	Firm	261	0.32	0.72
Parent IT trademarks	# trademarks held by parent (largest) of the startup at entry.	Firm	286	1.07	1.89
Serial		Firm	286	0.08	
Related startups		Firm	286	0.49	
Unrelated startups		Firm	286	0.25	
Other entrepreneurs		Firm	286	0.09	
Number of founders		Firm	286	1.53	0.86
Submarket dummies	antivirus, firewall, network software, authentication, hardware, encryption and parental control. The left-out category is consulting.	submarket	286		
Industry age	Age of the industry measured from 1970.	Year	286	8.87	5.68
Firm age	=current year - ISM entry year.	Firm, year	286	6.88	4.94
Internet bust years	=1 if the startup entered in 2001 or later..	Firm	286	0.45	-

[a] For 14 startups we were unable to trace outcomes.
[b] Founder histories for a total of 25 startups could not be traced. Of these, 10 did not report initial scale.
[c] A total of 37 startups do not report their initial size.

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)	0.31	0.39	0.24	0.15	0.15	0.14	0.10	0.04
	(0.04)	(0.05)	(0.05)	(0.07)	(0.03)	(0.05)	(0.03)	(0.06)
Low Quality(2)	0.09	0.15	0.08	0.07	0.27	0.33	0.19	0.14
	(0.02)	(0.05)	(0.04)	(0.06)	(0.02)	(0.06)	(0.04)	(0.07)
(1)-(2)	0.22	0.24	0.16	0.08	-0.12	-0.19	-0.09	-0.10
	(0.04)	(0.07)	(0.06)	(0.10)	(0.04)	(0.08)	(0.05)	(0.09)
Overall		0.26	0.16	0.10		0.25	0.16	0.09
		(0.04)	(0.03)	(0.05)		(0.05)	(0.03)	(0.06)

Notes:
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 below average. The standard errors are provided in parentheses. N=272

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

	Baseline (1)		VC controls (2)		With avg. scale and avg. exp. for missing values (3)		Unobs heterog. non-parametric (4)	
	Failure	Success	Failure	Success	Failure	Success	Failure	Success
Log(1+ work. exp)	0.20 ***	0.16 ***	0.17 ***	0.19 ***	0.17 ***	0.15 ***	0.19 ***	0.14 ***
	(0.05)	(0.03)	(0.03)	(0.05)	(0.03)	(0.06)	(0.03)	(0.05)
Internet bust years	-0.79 ***	-0.74 ***	-0.73 ***	-0.78 ***	-0.83 ***	-0.71 ***	-0.78 ***	-0.77 ***
	(0.21)	(0.26)	(0.24)	(0.25)	(0.32)	(0.26)	(0.32)	(0.35)
Log(1+patents)	-0.14 ***	0.08 **	-0.15 *	0.07 ***	-0.20 ***	0.12 *	-0.16 ***	0.13 *
	(0.05)	(0.04)	(0.06)	(0.02)	(0.04)	(0.08)	(0.04)	(0.08)
Log(initial scale)	-0.16 ***	0.49 ***	-0.17 ***	0.55 ***	-0.25 ***	0.51 ***	-0.19 ***	0.62 ***
	(0.05)	(0.09)	(0.05)	(0.11)	(0.05)	(0.13)	(0.02)	(0.12)
Log(1+parents IT TM)	-0.19 ***	0.14 ***	-0.19 ***	0.16 **	-0.15 **	0.26 **	-0.18 *	0.22 *
	(0.07)	(0.04)	(0.10)	(0.03)	(0.07)	(0.09)	(0.10)	(0.11)
Related startup	-0.03	0.17	-0.02	0.18	-0.04	0.24 ***	-0.08	0.19
	(0.09)	(0.19)	(0.09)	(0.21)	(0.14)	(0.18)	(0.06)	(0.20)
Unrelated startup	-0.04	0.21	-0.04	0.19	-0.02	0.21	-0.03	0.21
	(0.15)	(0.21)	(0.14)	(0.24)	(0.09)	(0.24)	(0.03)	(0.20)
Serial	0.71 **	0.65 **	0.79 ***	0.64 *	0.86 ***	0.86 ***	0.72 ***	0.87 ***
	(0.37)	(0.30)	(0.30)	(0.37)	(0.37)	(0.35)	(0.27)	(0.30)
Other	0.51	-0.25 *	0.54	-0.25	0.60 *	-0.36	0.49	-0.39
	(0.38)	(0.15)	(0.37)	(0.16)	(0.36)	(0.22)	(0.32)	(0.44)
No. of entrep.	-0.13 *	0.27 ***	-0.09 *	0.23 *	-0.13 **	0.23	-0.09	0.15 **
	(0.08)	(0.06)	(0.05)	(0.13)	(0.06)	(0.15)	(0.05)	(0.07)
Constant	-4.16 ***	-5.03 ***	-4.73 ***	-5.93 ***	-3.24 ***	-5.83 ***	-4.27 ***	-4.98 ***
	(0.99)	(0.56)	(1.20)	(2.04)	(1.13)	(1.69)	(1.45)	(1.01)
N†	2117 (249)		2117 (249)		2551 (272)		2117 (249)	
LL	-436.17		-434.31		-463.63		-438.26	
Variance	2.15 (1.50)		1.94 (1.37)		1.90 (1.49)			
Location parameters							0.44, -2.28, 2.52, -0.02	
Probability							0.07, 0.08,0.17, 0.68	
(VC and CVC dummies)	N		Y		N		N	

Notes. Standard errors are in parentheses, cluster corrected by firm. The unit of observation is firm-year. Among firms for which we were able to trace outcomes, 23 firms did not report initial scale and for 11 firms we could not trace founder histories. All specifications include firm age, (firm age)$_2$, industry age, (industry age)$_2$, and seven submarket dummies.

[a]Number of firms in parentheses.*Significant at 10%; **significant at 5%; ***significant at 1%.

Table 5: Competing hazard regressions of failure or cash-out, by high and low venture quality

	Low quality(1)		High Quality(1)		With interactions(2)	
	Failure	Success	Failure	Success	Failure	Success
Log(1+work exp)	0.28**	0.06***	0.07**	0.76***	0.68**	0.06**
	(0.12)	(0.02)	(0.03)	(0.15)	(0.30)	(0.03)
Log(initial size)					-0.35***	0.24***
					(0.08)	(0.09)
Log(1+work exp)*log(init.size)					-0.14***	0.03**
					(0.06)	(0.01)
Internet bust years	-0.86**	-0.48***	-0.42***	-1.12***	-0.84***	-0.76***
	(0.43)	(0.14)	(0.13)	(0.23)	(0.17)	(0.22)
Log(1+patents)	-0.33***	0.04**	-0.07*	0.17***	-0.18*	0.13**
	(0.08)	(0.02)	(0.01)	(0.02)	(0.10)	(0.06)
Log(1+parents IT TM)	-0.14**\	0.19***	-0.50***	0.24***	-0.25***	0.21***
	(0.07)	(0.02)	(0.12)	(0.07)	(0.09)	(0.09)
Related startup	0.25	0.13	0.27	0.18	-0.03	-0.48
	(0.34)	(0.20)	(0.36)	(0.39)	(0.14)	(0.54)
Unrelated startup	0.34	0.21	0.32	0.26	-0.05	0.64
	(0.43)	(0.38)	(0.53)	(0.43)	(0.09)	(0.44)
Serial	0.29***	1.26***	0.50***	0.67***	0.77**	0.69*
	(0.07)	(0.15)	(0.07)	(0.14)	(0.33)	(0.36)
Other	0.38***	-0.05	0.76	-0.49	0.51	-0.36
	(0.04)	(0.10)	(0.88)	(0.37)	(0.47)	(0.39)
No. of founders	-0.66***	0.35**	-0.39***	0.24***	-0.09*	0.33***
	(0.18)	(0.18)	(0.11)	(0.08)	(0.05)	(0.10)
Constant	-7.58***	-9.66***	-4.28***	5.70***	-4.70***	-10.04***
	(1.42)	(1.68)	(1.55)	(1.05)	(1.91)	(1.14)
N	1149(131)		968(118)		2117(249)	
Submarket dummies(7)	Y		Y		Y	
LL	-142.83		-124.78		-459.85	
Variance	1.91 (1.24)		1.96 (1.48)		2.34 (1.62)	

Notes: [†]Number of firms in parentheses. High Quality: Startups with initial scale above the average. Low Quality: Startups with initial scale below average.

Table 6: Robustness checks. Competing hazard regressions of failure or cash-out using other measures of opportunity cost

	BLS wages (industry and occupation) as opp. cost measure (1)		Founder patents as opportunity cost measure (2)	
	Failure	Success	Failure	Success
Log(1+ founder patents)			0.17 **	0.16 **
			(0.08)	(0.03)
Log(wages)	0.91 ***	1.19 ***		
	(0.26)	(0.31)		
Internet bust years	-0.81 ***	-0.73 **	-0.70 ***	-0.63 ***
	(0.30)	(0.34)	(0.19)	(0.21)
Log(1+patents)	-0.29 ***	0.19 **	-0.23 ***	0.21
	(0.09)	(0.06)	(0.09)	(0.14)
Log (initial scale)	-0.28 ***	0.41 ***	-0.24 ***	0.27 ***
	(0.09)	(0.11)	(0.04)	(0.11)
Log(1+parents' IT TM)	-0.34 ***	0.28	-0.31 *	0.21
	(0.10)	(0.20)	(0.18)	(0.18)
Related startup	0.03	0.25	-0.09	0.11
	(0.08)	(0.37)	(0.06)	(0.16)
Unrelated startup	0.03	0.29	-0.04	0.07
	(0.05)	(0.30)	(0.06)	(0.08)
Serial	0.62 **	0.70 *	0.69 ***	0.78 ***
	(0.17)	(0.21)	(0.27)	(0.27)
Other	0.67	-0.41	0.54	-0.39
	(0.47)	(0.52)	(0.32)	(0.42)
No. of founders	-0.16 *	0.31 ***	-0.21 ***	0.29 **
	(0.09)	(0.12)	(0.07)	(0.14)
Constant	-4.77 ***	-6.42 ***	-4.69 ***	-5.78 ***
	(1.06)	(0.75)	(1.07)	(0.92)
N†	2117 (249)		2117 (249)	
LL	-429.37		-434.52	
Variance	1.15 (0.94)		1.66 (1.16)	

Notes: †Number of firms in parentheses. ***Significant at 1%. ** Significant at 5%. * Significant at 10%. Standard errors in parentheses, cluster corrected by firm. The unit of observation is firm, year. All specifications include firm age, (firm age)^2, industry age, (industry age)^2, and 7 submarket dummies.

Table 7: Robustness Checks: Testing for competing hypotheses regarding risk bearing and entrepreneurial ability to discern. Competing hazard regressions of failure or cash-out

	Related startup(1)		Unrelated Startup(1)		With coeff. of variation (2)		With lag growth (3)	
	Failure	Success	Failure	Success	Failure	Success	Failure	Success
Log(1+work exp)	0.22***	0.15***	0.23***	0.18***	0.19***	0.20***	0.04	0.05
	(0.09)	(0.03)	(0.08)	(0.08)	(0.04)	(0.04)	(0.03)	(0.04)
Lag employee growth							0.19***	0.21***
							(0.05)	(0.07)
Internet bust years	-0.78***	-0.68***	-0.68***	-0.59	-0.64***	-0.70**	-0.71***	-0.69***
	(0.31)	(0.23)	(0.22)	(0.27)	(0.21)	(0.24)	(0.22)	(0.29)
Log(1+patents)	-0.16**	0.15	-0.36**	0.21***	-0.21***	0.10	-0.14***	0.06*
	(0.08)	(0.12)	(0.16)	(0.09)	(0.04)	(0.05)	(0.04)	(0.04)
Log(initial size)	-0.15*	0.28**	-0.20***	0.18***	-0.26***	0.53***	-0.15***	0.61***
	(0.09)	(0.13)	(0.10)	(0.06)	(0.07)	(0.14)	(0.04)	(0.05)
Log(1+parents IT TM)	-0.20*	0.17***	-0.19***	0.12	-0.18*	0.07***	-0.38***	0.15*
	(0.12)	(0.06)	(0.04)	(0.11)	(0.10)	(0.04)	(0.05)	(0.08)
Related startup					-0.06	0.10	-0.03	0.18
					(0.13)	(0.13)	(0.16)	(0.21)
Unrelated startup					-0.04	0.19	0.05	0.21
					(0.09)	(0.32)	(0.13)	(0.23)
Serial					0.62***	0.67***	0.69***	0.72***
					(0.26)	(0.22)	(0.25)	(0.24)
Other					0.41*	-0.18	0.61*	-0.32
					(0.23)	(0.14)	(0.37)	(0.21)
No. of founders	-0.18	0.21	-0.04	0.05	-0.14**	0.30***	-0.11*	0.18***
	(0.15)	(0.18)	(0.11)	(0.07)	(0.06)	(0.12)	(0.05)	(0.06)
Coef. of variation					2.79***	2.81***		
					(0.21)	(0.32)		
Constant	-4.73***	-5.66***	-4.87***	-5.23***	-6.49***	-6.15***	-4.81***	-5.48***
	(1.79)	(1.31)	- (1.87)	(1.15)	(1.27)	(2.40)	(0.70)	(0.96)
N	1194 (136)		587 (69)		2074 (244)		1830 (244)	
Submarket dummies(7)	Y		Y		Y		Y	
LL	-222.03		-136.23		-421.23		-404.12	
Variance	1.70 (1.21)		2.10 (1.89)		2.20 (1.26)		1.76 (1.26)	

Notes: †Number of firms in parentheses. ***Significant at 1%. ** Significant at 5%. * Significant at 10%. Standard errors in parentheses, cluster corrected by firm. The unit of observation is firm, year. All specifications include firm age, (firm age)^2, industry age, (industry age)^2, and 7 submarket dummies. RELATED startups are those with founders from IT industries (Software, hardware, semiconductors and telecommunication); UNRELATED startups are from all other industries. The Coefficient of Variation is the ratio of the standard deviation to the average, of employment for the first three years of the startups life. Lagged growth is the lagged one period growth in employment.

Graphical interpretation of interaction terms in specification 2 of Table 5

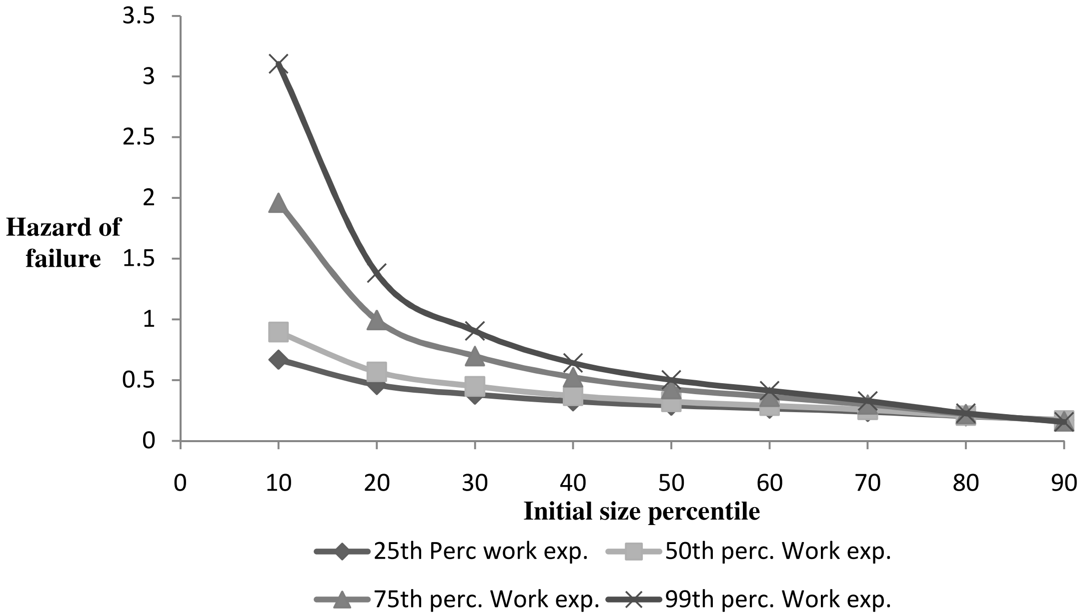

Figure 1A Relative hazard of failure for different values of work exp. and initial size

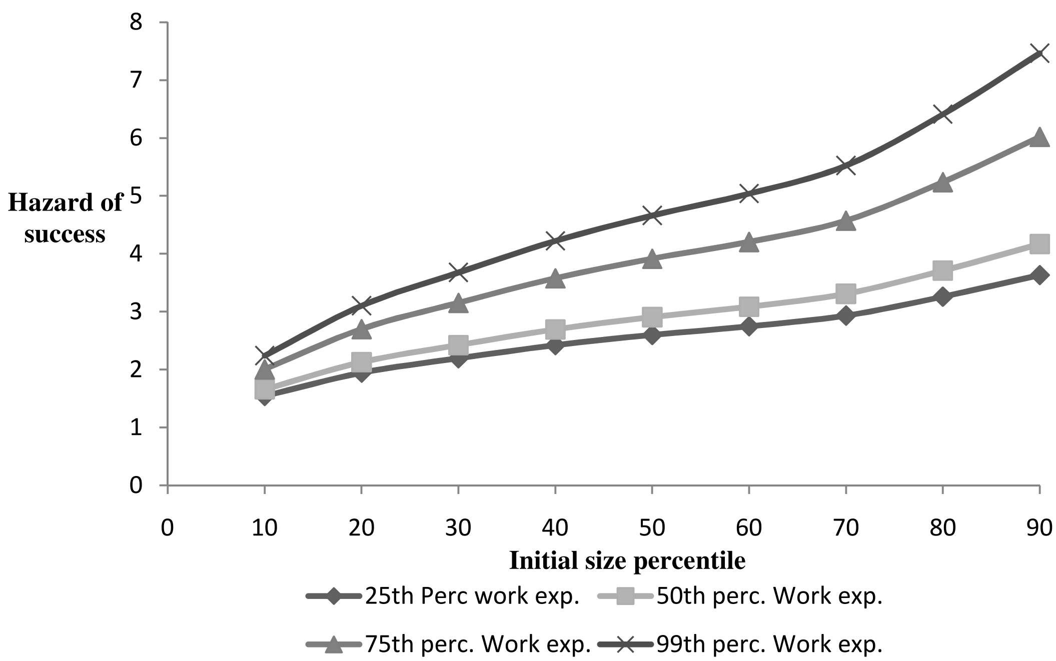

Figure 1B Relative hazard of success for different values of work exp. and initial size

APPENDIX -1

Proof of propositions:

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

   $\frac{\partial V}{\partial m} = PJ - \beta V - m = 0$ and $V = \frac{\frac{m^2}{2} + \alpha - mPJ}{\beta(1-m)}$. 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 is $V = \frac{(1-\beta(1-PJ))-A^{1/2}}{\beta^2}$ 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 $0 \leq m^* \leq 1$.

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

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

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

   If V>0, we need $\left(\beta^2 - \beta(1-PJ)\right) > A^{1/2}$ and $J > 1$, which are satisfied for J large enough.

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. $\frac{\partial m^*}{\partial P} = \frac{A^{-\frac{1}{2}}}{2\beta}\frac{\partial A}{\partial P} = A^{-\frac{1}{2}}J[1-\beta] > 0$

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

   $\frac{\partial \Phi}{\partial P} = m^* + P\frac{\partial m^*}{\partial p}$. Since $\frac{\partial m^*}{\partial P} => 0, \frac{\partial \Phi}{\partial P} > 0$

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

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

   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 low values of P, it is increasing in P.

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

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

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

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

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

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

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

Also

$$\frac{\partial^2\Phi}{\partial\alpha\partial P} = P\frac{\partial^2 m^*}{\partial\alpha\partial P} + \frac{\partial P}{\partial\alpha}\frac{\partial m^*}{\partial\alpha}$$

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

$$\frac{\partial^2 m^*}{\partial P\partial\alpha} = -A^{-\frac{3}{2}}J(1-\beta)\beta^2$$

$$\frac{\partial^2\Phi}{\partial\alpha\partial P} = \frac{\beta}{A^{\frac{1}{2}}}\left[1 - \frac{\beta J(1-\beta)}{A}[1-p(1-p)] > 0\right]$$

Extension

Suppose the hazard of success *Pm* but the hazard of failure is (1-*P*)δ(*m*), where δ(*m*) is increasing and convex in m, i.e., δ'(*m*)>0 and δ''(*m*)>0. We also assume that $\frac{dln\delta}{d\delta} > 0$.

Define the probability of survival is given by X ≡ *1-Pm-(1-P)*δ(*m*).

1. We first show that the probability of success is $\frac{1}{1+A}$ and of failure is $1 - \frac{1}{1+A}$

   The probability of success is $Pm+XPm+X^2Pm+X^3mp = \frac{Pm}{1-X} \equiv \frac{1}{1+A}$ where A ≡ $\frac{(\mathbf{1}-\boldsymbol{P})\delta(\boldsymbol{m})}{\boldsymbol{Pm}}$

   The probability of failure is $1 - \frac{1}{1+A}$

2. The probability of success is increasing in m.

   The probability of success is $\frac{1}{1+A} \equiv S$

   $$\frac{\partial S}{\partial m} = -(1+A)^2.\frac{\partial A}{\partial m}$$

   $$\frac{\partial A}{\partial m} = P(1-P)[m\delta'(m) - \delta(m)] > 0$$

   Hence $\frac{\partial S}{\partial m} < 0$

3. The probability of failure is decreasing in m.

   The probability of failure is $1 - \frac{1}{1+A} \equiv F$

   $$\frac{\partial F}{\partial m} = -\frac{\partial S}{\partial m} > 0$$

The entrepreneur's objective function is $V = Max_m \{mpJ + \beta VX - c(m) - \alpha\}$

The FOC is given by $\frac{\partial V}{\partial m} = pJ - \beta \frac{\partial X}{\partial m} = c'(m)$ (a)

where $\frac{\partial X}{\partial m} = -(p + (1-p)\delta'(m))$

$$V = \frac{mpJ - c(m) - \alpha}{1 - \beta X} \quad \text{(b)}$$

4. We show that $\frac{\partial^2 V}{\partial m^2} < 0$

   Using (a) $\frac{\partial^2 V}{\partial m^2} = -\beta\big(p + (1-p)\delta'(m)\big)\frac{\partial V}{\partial m} - \beta V(1-p)\delta''(m) - c''(m)$

   Since $\frac{\partial V}{\partial m} = 0$ this is just $-\beta V(1-p)\delta''(m) - c''(m) < 0$

5. We now show that $\frac{\partial^2 V}{\partial m \partial p} > 0$

   $$\frac{\partial^2 V}{\partial m \partial p} = J - \beta\big(p + (1-p)\delta'(m)\big).\frac{\partial V}{\partial p} - \beta V(1 - \delta'(m))$$

   Note that $\frac{\partial V}{\partial p} = \frac{(1-\beta X)mJ + (mpJ - c(m) - \alpha)\beta(\delta(m) - m))}{(1-\beta X)^2}$

   Using (b) above, this is $\frac{\partial V}{\partial p} = \frac{(1-\beta X)mJ + (1-\beta X)\beta(\delta(m) - m))}{(1-\beta X)^2}$

   $$\frac{\partial^2 V}{\partial m \partial p} = J\left[1 - \frac{m\beta\big(p + (1-p)\delta'(m)\big)}{1-\beta X}\right] - \beta V\left[1 - \delta'(m) + \frac{\beta\big(p + (1-p)\delta' m)(\delta(m) - m)}{1-\beta X}\right]$$

   $\equiv J\lambda - \beta V\tau$

   Collecting terms $\lambda = \frac{1 - \beta(2mp - (1-P)\big(\delta(m) + (\delta'(m)\big)^2 - m\delta'(m))}{(1-\beta X)}$

   $$\tau = \frac{1 - \beta(1 - 2mp) - (1-p)\big(\delta(m) + (\delta'(m)\big)^2 - m\delta'(m))}{1-\beta X} - \frac{(1-\beta X)\delta'(m) + \beta\big(p + (1-P)\delta'(m)\big)(\delta'(m) - m)}{1-\beta X}$$

   Since that second term in τ is negative, λ > τ. Moreover J > βV. This implies that $\frac{\partial V}{\partial m \partial p} > 0$

6. m^* is increasing in α, or $\frac{\partial m^*}{\partial \alpha} > 0$

   $\frac{\partial m^*}{\partial \alpha} = -\frac{\partial^2 V}{\partial m \partial \alpha} \Big/ \frac{\partial^2 V}{\partial m^2}$. Using (b) $\frac{\partial V}{\partial \alpha} = -\frac{1}{1-\beta X}$ and $\frac{\partial^2 V}{\partial \alpha \partial m} = \frac{\beta(p + (1-p)\delta'(m))}{(1-\beta X)^2} > 0$

   We have already shown that $\frac{\partial^2 V}{\partial m^2} < 0$. Thus $\frac{\partial m^*}{\partial \alpha} > 0$.

Once again, let Φ denote that hazard of exit. $\Phi = m^* p$. Similarly, let Ω denote the hazard of failure which equals $\delta(m^*)(1-p)$

7. $\frac{\partial \Phi}{\partial \alpha} > 0.$

   It follows that $\frac{\partial \Phi}{\partial \alpha} = \frac{\partial m^*}{\partial \alpha} p = \frac{p\beta(p+(1-p)\delta'(m))}{(\beta V((1-p)\delta''(m)+c''(m))(1-\beta X)^2} > 0$

8. $\frac{\partial \Omega}{\partial \alpha} > 0.$

   $$\frac{\partial \Omega}{\partial \alpha} = \frac{\partial m^*}{\partial \alpha}(1-p) = \frac{(1-p)\beta(p+(1-p)\delta'(m))}{(\beta V\big((1-p)\delta''(m)+c''(m)\big)(1-\beta X)^2} > 0$$

9. $\frac{\partial \Phi}{\partial p} > 0.$

   $$\frac{\partial \Phi}{\partial p} = p.\frac{\partial m^*}{\partial p} + m^*.\frac{\partial m^*}{\partial p} = \frac{-\frac{\partial^2 V}{\partial m \partial p}}{\frac{\partial^2 V}{\partial m^2}}.$$

We have already shown that the numerator is positive and that the denominator is negative. Thus $\frac{\partial m^*}{\partial p} > 0$ which implies that $\frac{\partial \Phi}{\partial p} > 0$

10. $\frac{\partial \Omega}{\partial p}$ cannot be signed.

    $\frac{\partial \Omega}{\partial p} = -\delta(m^*) + (1-p)\delta'(m^*).\frac{\partial m^*}{\partial p}$ which cannot be signed.

11. We now show that $\frac{\partial \Phi}{\partial \alpha \partial p} > 0.$

From (5) above, $\frac{\partial \Phi}{\partial \alpha} = \frac{p\beta(p+(1-p)\delta'(m))}{(\beta V\big((1-p)\delta''(m)+c''(m)\big)(1-\beta X)^2} \equiv \frac{N}{D}$

$$\frac{\partial^2 \Phi}{\partial \alpha \partial p} = \frac{D\beta\left[\big(p+(1-p)\delta'(m)\big)+p(1-\delta'(m))\right]+N\left[\beta V\ (1-\beta X)^2\delta''(m)+2(1-\beta X)(\beta V\big((1-p)\delta''(m)+c''(m)\big)\beta(\delta'(m)-m)\right]}{D^2} > 0.$$

12. $\frac{\partial \Omega}{\partial \alpha \partial p} > 0$

From (5) above, $\frac{\partial \Omega}{\partial \alpha} = \frac{(1-p)\beta(p+(1-p)\delta'(m))}{(\beta V\big((1-p)\delta''(m)+c''(m)\big)(1-\beta X)^2} \equiv \frac{N_1}{D_1}$

$$\frac{\partial^2 \Phi}{\partial \alpha \partial p} = \frac{D_1\beta\left[-\big(p+(1-p)\delta'(m)\big)+(1-p)(1-\delta'(m))\right]+N_1\left[\beta V\ (1-\beta X)^2\delta''(m)+2(1-\beta X)(\beta V\big((1-p)\delta''(m)+c''(m)\big)\beta(\delta'(m)-m)\right]}{D^2}$$

whose sign is ambiguous.