Cash-Out or Flameout! Opportunity Cost and Entrepreneurial Strategy: Theory, and Evidence from the Information Security Industry

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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 data set of information security start-ups, 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.

Key words: entrepreneurship; opportunity costs; performance

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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, perhaps, a different start-up) 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 start-up. It can fail (i.e., be dissolved) or it can cash out (have an initial public offering (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 start-up 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.1 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

1 The investment made by the start-up 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.
intuition using a hand-collected data set of start-ups (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 §3, we develop a formal model and develop testable implications. In §4, we explain the data sources for our empirical analysis. Section 5 contains the results of the empirical analysis. We conclude in §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 enough to compensate for the opportunity cost (Shane and Venkataraman 2000). Amit et al. (1995) show that potential entrepreneurs with high opportunity costs are less likely to select into entrepreneurship. Boden and Nucci (2000) find that start-ups in poor economic times have 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

Whereas 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 et al. (1997) estimate a model of entrepreneurial performance where entrepreneurial human capital increases both the income and the threshold of acceptable profitability. In Gimeno et al. (1977), exit takes place when profits fall below threshold, whereas 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, 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, 1996) formulation would suggest that failing firms are poor-quality firms, and thus would grow less quickly, in our model, start-ups that fail quickly are also more likely to grow 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 preentry 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. 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 preentry 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 preentry 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, preentry work experience would result in quicker 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 information technology (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 start-up 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 that 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 start-up, a more experienced founder is likely to be associated with a riskier project, but only for start-ups from the IT industry itself. For start-ups 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 start-ups. As an additional robustness check, we directly control for 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. 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 start-up (which measures how plentiful outside employment opportunities are). We also separately control for whether the start-up receives venture capital financing, and for serial entrepreneurship (which might also control for wealth effects).

2.5. Founding Teams

Start-ups 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). 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 start-up (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.

3 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.
2.6. Investors
Investors may affect how aggressively the start-up seeks to cash out. For instance, Goldfarb et al. (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 $\alpha$ for every period the firm survives, and $\beta$ ($0 \leq \beta \leq 1$) 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 $Pm((1 - m) + (1 - m)^2 + (1 - m)^3 + \cdots) = P$.

Let $c(m) \equiv m^2/2$. The expected profit of an entrepreneur with opportunity cost of $\alpha$ is given by

$$V = \max_m \left\{ mP + \beta V(1 - m) - \frac{m^2}{2} - \alpha \right\}. \tag{1}$$

Let $m^*$ denote value that maximizes (1). The first-order condition implies that the optimal $m$, is

$$P\beta V - m = 0. \tag{2}$$

Rearranging, imposing $0 < m < 1$ and writing

$$A \equiv (1 - \beta(1 - P))^2 + 2\beta^2 \left( \alpha - \frac{P^2 I^2}{2} \right),$$

the first-order condition implies that the optimal $m$, is

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

Note that $A$ is increasing in $\alpha$, and $m^*$ is increasing in $A$, so that $m^*$ is increasing in $\alpha$ (all proofs are shown in the appendix).

**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 $\alpha$. Therefore, the hazard of cash-out also increases in $\alpha$.

**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 Result 1 implies that hazard of failure increases with $\alpha$ as well.

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

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The results hold as long a $C(m)$ is convex in $m$.

Note that because $0 \leq m \leq 1$, $A^{1/2}$ is bounded between $1 - \beta$ and 1.
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.

**Result 2.** Higher quality ventures have higher \( m \).

Because \( m^* \) 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 the appendix that \( \frac{\partial^2 \Omega}{\partial \alpha \partial P} > 0 \). 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. Although 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, whereas 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 the online appendix, available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1824284). For instance, if one lets the hazard of success be \( Pm \) as before but then the hazard 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 \( B \equiv (1 - P)\delta(m)/Pm \), which decreases with \( m \) as \( \delta(m) \) 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.\(^6\) 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 start-ups, 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 start-ups that entered ISM between 1989 and 2004. Although 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, start-ups 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 data set with information about the founders (up to four founders of each start-up) from a variety of publicly available data sources on the Internet such as ZoomInfo (http://www.zoominfo.com), LinkedIn (http://www.linkedin.com), Google Archives (http://news.google.com/archivesearch), Internet Archive (http://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 start-up.

4.1. Cash-Out and Failure

**Failure.** We first identified whether a start-up had exited using the CorpTech database.\(^7\) We then iden-
tified a start-up 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 start-ups, if the transaction value (the value of the acquisition deal) was less than the total capital raised; (ii) if a start-up was not VC funded and reported a loss in the year prior to the acquisition; (iii) if the start-up is not VC-funded and we lack profitability data, if none of the founders of the focal start-up 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 start-up were untraceable.

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

Cash-out. We define cash-out as a favorable acquisition (an acquisition of a VC-funded start-up whose transaction value exceeded total capital raised, or an acquisition of a non-VC-funded start-up that reported a profit in the year preceding acquisition, or, absent that data, acquisition of a non-VC-funded start-up that resulted in at least one of the founders joining the acquiring firm) or an 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.

### 4.2. 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 start-up. 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 start-up was established.\(^8\) We obtained this variable by matching the prior job description and industry of every founder of the focal start-up with the closest industry and job description match in

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**Table 1** Classification of Outcomes

<table>
<thead>
<tr>
<th>Description</th>
<th>How defined</th>
<th>No.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total surviving start-ups (neither success nor failure) (A)</td>
<td>Press report clearly said that the acquisition was distress</td>
<td>161</td>
</tr>
<tr>
<td>Bankruptcy or asset sale (B)</td>
<td>VC-funded firms if transaction value was less than total capital raised (available for all VC-funded start-ups and 11 in all)</td>
<td>10</td>
</tr>
<tr>
<td>Unfavorable acquisitions (C)</td>
<td>Non-VC-funded firms (a) if the focal start-up 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)</td>
<td>43</td>
</tr>
<tr>
<td>Favorable acquisitions (D)</td>
<td>VC-funded firms if transaction value was higher than or equal to the total capital raised (available for all VC-funded start-ups and 17 in all)</td>
<td>22</td>
</tr>
<tr>
<td>Total acquisitions (E = C + D)</td>
<td>Corptech/VX database</td>
<td>65</td>
</tr>
<tr>
<td>IPOs (F)</td>
<td></td>
<td>36</td>
</tr>
<tr>
<td>Total failures (G = B + C)</td>
<td></td>
<td>53</td>
</tr>
<tr>
<td>Total success (H = D + F)</td>
<td></td>
<td>58</td>
</tr>
<tr>
<td>Acquisitions that could not be classified as cash-outs or failure (not used in empirical analysis)</td>
<td></td>
<td>14</td>
</tr>
<tr>
<td>Total start-ups (I = A + G + H)</td>
<td></td>
<td>286</td>
</tr>
</tbody>
</table>

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\(^8\) Using the average experience and average wages yielded qualitatively similar results.
the Bureau of Labor Statistics (BLS) Occupational Employment Statistics (OES) database for the year in which the focal start-up was established. For firms with multiple founders, we take the maximum of the wages of all founders of the focal start-up. The matching of industries, and of job descriptions, both require judgments, especially since job descriptions of founders (prior to the start-up) were obtained from sources such as LinkedIn.9

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 (see Fairlie and Chatterji 2008).

Inssofar 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 start-up, 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.10

4.3. 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 start-ups. 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, b; Dunne et al. 1988, 1989; Phillips and Kirchhoff 1989; Audretsch and Mahmood 1995; Mata et al. 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 start-ups by the number of IT trademarks of the previous employer of the founder (parent IT trademarks, henceforth) at the time of entry.11 This measure is valid insofar as the founder “inherited” some of the marketing ability from the earlier employer. In cases where the start-up had multiple parents, we use numbers from the parent with the greatest number of IT trademarks. Hsu and Ziedonis (2007) argue that the number of patents of start-ups 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 start-up 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.

4.4. Controls

Market-segment fixed effects. We use seven market-segment fixed effects: encryption products, network security, authentication, firewalls, antivirus, spam control, and hardware, with consulting being the residual market segment.12

Firm age. This variable is measured as the number of calendar years from the year of entry until the year of failure, cash-out, or 2004, whichever is 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 nonlinearities, we also include the square term.

Industry age. 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.

Entrant type. We classified start-ups into one or more of the following categories based on the immediate prior experience of founders: related start-ups (founded by employees of computer hardware, software, IT consultancies, telecommunication firms, or ISM firms); unrelated start-ups (founders from defense, finance, aerospace, and automobile industries); serial start-ups (start-ups founded by serial founders); and other start-ups (those with founders from universities, military, or government). The left-out category is of the firms with founders with untraceable backgrounds and hackers.

Source of capital. In many of our specifications we also control for the source of capital of start-ups (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.

9 We assigned the maximum wages in our data set for founders that were entrepreneurs immediately prior to founding the focal ISM start-up and minimum wage of the OES database where the founder had no experience.

10 Founder patents may also measure firm quality, but because 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.

11 We searched the U.S. Patent and Trademark Office trademarks database (http://tess2.uspto.gov/bin/gate.exe?f=tess&state =4007:8ekfjil.1) 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”).

12 Note that we only measure the segment of entry.
Table 2  Description of Measures Used

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Level</th>
<th>N</th>
<th>Mean</th>
<th>Std. dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Failure</td>
<td>=1 if the start-up went into a distress sale or went out of business completely</td>
<td>Firm</td>
<td>272a</td>
<td>0.20</td>
<td></td>
</tr>
<tr>
<td>Cash-out</td>
<td>=1 if the start-up was acquired on favorable terms or had an IPO</td>
<td>Firm</td>
<td>272a</td>
<td>0.21</td>
<td></td>
</tr>
<tr>
<td>Work experience</td>
<td>$\log(1 + \text{no. of years of work experience})$ of the main founder; measure of opportunity cost</td>
<td>Firm</td>
<td>261a</td>
<td>1.27</td>
<td>1.63</td>
</tr>
<tr>
<td>Founder patents</td>
<td>$\log(1 + \text{no. of patents})$ held by the founder that had the most patents among all founders of the focal start-up; measure of opportunity cost</td>
<td>Firm</td>
<td>261</td>
<td>0.32</td>
<td>0.72</td>
</tr>
<tr>
<td>Wages</td>
<td>$\log(1 + \text{wages})$ of the founder of the start-up; max. of the wages if multiple founders; this is yet another proxy for opportunity cost</td>
<td>Firm</td>
<td>261</td>
<td>11.24</td>
<td>5.12</td>
</tr>
<tr>
<td>Initial scale</td>
<td>$\log(1 + \text{no. of employees of the start-up at the time of entry})$; this is our proxy for the quality of the start-up</td>
<td>Firm</td>
<td>249c</td>
<td>3.59</td>
<td>1.41</td>
</tr>
<tr>
<td>Security patents</td>
<td>$\log(1 + \text{no. of forward citations weighted security patents held by a firm at entry}}$; this variable proxies technical capability</td>
<td>Firm</td>
<td>286</td>
<td>0.32</td>
<td>0.74</td>
</tr>
<tr>
<td>Founder patents</td>
<td>$\log(1 + \text{no. of patents held by the main founder of the focal start-up})$</td>
<td>Firm</td>
<td>261</td>
<td>0.32</td>
<td>0.72</td>
</tr>
<tr>
<td>Parent IT trademarks</td>
<td>No. of trademarks held by parent (largest) of the start-up at entry</td>
<td>Firm</td>
<td>286</td>
<td>1.07</td>
<td>1.89</td>
</tr>
<tr>
<td>Serial</td>
<td></td>
<td>Firm</td>
<td>286</td>
<td>0.08</td>
<td></td>
</tr>
<tr>
<td>Related start-ups</td>
<td></td>
<td>Firm</td>
<td>286</td>
<td>0.49</td>
<td></td>
</tr>
<tr>
<td>Unrelated start-ups</td>
<td></td>
<td>Firm</td>
<td>286</td>
<td>0.25</td>
<td></td>
</tr>
<tr>
<td>Other entrepreneurs</td>
<td></td>
<td>Firm</td>
<td>286</td>
<td>0.09</td>
<td></td>
</tr>
<tr>
<td>Number of founders</td>
<td></td>
<td>Firm</td>
<td>286</td>
<td>1.53</td>
<td>0.86</td>
</tr>
<tr>
<td>Submarket dummies</td>
<td>Antivirus, firewall, network software, authentication,</td>
<td>Submarket</td>
<td>286</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>hardware, encryption, and parental control; the left-out category is consulting</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Industry age</td>
<td>Age of the industry measured from 1970</td>
<td>Year</td>
<td>286</td>
<td>8.87</td>
<td>5.68</td>
</tr>
<tr>
<td>Firm age</td>
<td>=current year − ISM entry year</td>
<td>Firm-year</td>
<td>286</td>
<td>6.88</td>
<td>4.94</td>
</tr>
<tr>
<td>Internet bust years</td>
<td>=1 if the start-up entered in 2001 or later</td>
<td>Firm</td>
<td>286</td>
<td>0.45</td>
<td>—</td>
</tr>
</tbody>
</table>

"aFor 14 start-ups we were unable to trace outcomes.  
"bFounder histories for a total of 25 start-ups could not be traced.  
"cA total of 37 start-ups do not report their initial size.

**Number of founders.** 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 start-ups 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.

5. **Empirical Analysis**

5.1. **Nonparametric Analysis**

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 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 column (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
yield qualitatively similar results. Comparing rows (1) and (2) in column (e-f) shows that the difference in failure share is increase with opportunity cost more slowly for higher quality ventures. Comparing rows (1) and (2) in column (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.

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. Furthermore, 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 et al. (2005), we implement a discrete time-hazard regressions specification also used in Martin and Mitchell (1998) and King and Tucci (2002).13

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 §3.5) would allow the probability of cash-out and failure to also depend upon m_i. This more general specification suggests a multinomial logit with unobserved heterogeneity. Thus, in our baseline specification, the probability of cash-out for the ith firm is \( \text{exp}(X_i \beta_c + u_{ic})/(1 + \text{exp}(X_i \beta_c + u_{ic}) + \text{exp}(X_i \beta_f + u_{if})) \), where \( X_i \) represents the observed characteristics of the entrepreneur and venture, such as experience, start-up 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 \( \sigma \).

We use 2,117 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 firms14 because data on founder characteristics or, less frequently, on initial scale, were missing. Including the dropped observations by assigning the sample minimum size of two employees to firms that do not report initial size as well as a minimum work experience value of zero 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 start-ups formed after the Internet era

\[ \text{exp}(X_i \beta_c + u_{ic})/(1 + \text{exp}(X_i \beta_c + u_{ic}) + \text{exp}(X_i \beta_f + u_{if})) \]

\[ \text{exp}(X_i \beta_c + u_{ic})/(1 + \text{exp}(X_i \beta_c + u_{ic}) + \text{exp}(X_i \beta_f + u_{if})) \]

13 Continuous time specifications such as Cox proportional hazard yield qualitatively similar results.

14 Of 272 firms for which we could trace outcomes, 12 start-ups did not report initial size, although we were able to trace founder histories for these start-ups. For 11 start-ups neither founder histories nor initial sizes are available.
Table 4  Competing Hazard Regressions of Failure or Cash-Out

<table>
<thead>
<tr>
<th></th>
<th>Baseline (1)</th>
<th>VC controls (2)</th>
<th>With avg. scale and exp. for missing values (3)</th>
<th>Unobs heterog. non parametric (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Failure</td>
<td>Success</td>
<td>Failure</td>
<td>Success</td>
</tr>
<tr>
<td>Log(1 + work. exp.)</td>
<td>0.20***</td>
<td>0.16***</td>
<td>0.17***</td>
<td>0.19***</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td>(0.03)</td>
<td>(0.03)</td>
<td>(0.05)</td>
</tr>
<tr>
<td>Internet bust years</td>
<td>−0.79***</td>
<td>−0.74***</td>
<td>−0.73***</td>
<td>−0.78***</td>
</tr>
<tr>
<td></td>
<td>(0.21)</td>
<td>(0.26)</td>
<td>(0.24)</td>
<td>(0.25)</td>
</tr>
<tr>
<td>Log(1 + patents)</td>
<td>−0.14***</td>
<td>0.08**</td>
<td>−0.15**</td>
<td>0.07***</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td>(0.04)</td>
<td>(0.06)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Log(initial scale)</td>
<td>−0.16***</td>
<td>0.49**</td>
<td>−0.17***</td>
<td>0.55***</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td>(0.09)</td>
<td>(0.05)</td>
<td>(0.11)</td>
</tr>
<tr>
<td>Log(1 + parents IT TM)</td>
<td>−0.19***</td>
<td>0.14**</td>
<td>−0.19***</td>
<td>0.16**</td>
</tr>
<tr>
<td></td>
<td>(0.07)</td>
<td>(0.04)</td>
<td>(0.10)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>Related start-up</td>
<td>−0.03</td>
<td>0.17</td>
<td>−0.02</td>
<td>0.18</td>
</tr>
<tr>
<td></td>
<td>(0.09)</td>
<td>(0.19)</td>
<td>(0.09)</td>
<td>(0.21)</td>
</tr>
<tr>
<td>Unrelated start-up</td>
<td>−0.04</td>
<td>0.21</td>
<td>−0.04</td>
<td>0.19</td>
</tr>
<tr>
<td></td>
<td>(0.15)</td>
<td>(0.21)</td>
<td>(0.14)</td>
<td>(0.24)</td>
</tr>
<tr>
<td>Serial</td>
<td>0.71**</td>
<td>0.65**</td>
<td>0.79***</td>
<td>0.64**</td>
</tr>
<tr>
<td></td>
<td>(0.37)</td>
<td>(0.30)</td>
<td>(0.30)</td>
<td>(0.37)</td>
</tr>
<tr>
<td>Other</td>
<td>0.51</td>
<td>−0.25*</td>
<td>0.54</td>
<td>−0.25</td>
</tr>
<tr>
<td></td>
<td>(0.38)</td>
<td>(0.15)</td>
<td>(0.37)</td>
<td>(0.16)</td>
</tr>
<tr>
<td>No. of entrep.</td>
<td>−0.13*</td>
<td>0.27***</td>
<td>−0.09*</td>
<td>0.23*</td>
</tr>
<tr>
<td></td>
<td>(0.08)</td>
<td>(0.06)</td>
<td>(0.05)</td>
<td>(0.13)</td>
</tr>
<tr>
<td>Constant</td>
<td>−4.16***</td>
<td>−5.03***</td>
<td>−4.73***</td>
<td>−5.83***</td>
</tr>
<tr>
<td></td>
<td>(0.99)</td>
<td>(0.56)</td>
<td>(1.20)</td>
<td>(2.04)</td>
</tr>
</tbody>
</table>

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), industry age, (industry age), and seven submarket dummies.

N*: Number of firms in parentheses.

Significant at 10%; **significant at 5%; ***significant at 1%.

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.15 Also consistent with our theory, serial entrepreneurs have a higher hazard of cash-outs as well as failures.

Specification (2) of Table 4 includes controls for whether the start-up 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 because 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 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 nonparametrically, such as by allowing the $u_i$ and $u_j$ 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.\textsuperscript{16}

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 size. 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 (standard error = 0.12; $p = 0.01$).\textsuperscript{17} 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 (standard error = 0.17; $p = 0.00$).

In specification (2) of Table 5, we simply interact work experience and scale (instead of splitting the sample) and get similar results. In Figures 1 and 2, we interpret the interaction terms graphically by comparing the hazards of failure and cash-outs at different points in the work experience distribution. Figure 1 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)

\textsuperscript{16} Unreported specifications where we additionally control for education of the founders (e.g., whether the founder had a Ph.D., or an M.S. in computer science or electrical engineering) yield very similar results.

\textsuperscript{17} The standard errors for comparing coefficients in Table 5 are obtained by bootstrapping, based on 50 iterations.
by about 106%. However, for a start-up 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 start-ups. This result lends support to Prediction 6.

Figure 2 shows that the effect of experience on the hazard of success is larger for a start-up of higher quality relative to a start-up with lower quality. For a start-up 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 start-up 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.

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.

5.3.2. Alternative Interpretations of Work Experience. Risk taking and work experience. As noted in §2, entrepreneur opportunity cost may be correlated with project risk (and hence may condition hazards of

![Figure 1](image1.png)

**Figure 1** Relative Hazard of Failure for Different Values of Work Experience and Initial Size

![Figure 2](image2.png)

**Figure 2** Relative Hazard of Success for Different Values of Work Experience and Initial Size

<table>
<thead>
<tr>
<th>Table 6</th>
<th>Robustness Checks: Competing Hazard Regressions of Failure or Cash-Out Using Other Measures of Opportunity Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BLS wages (industry and occupation) as opportunity cost measure (1)</td>
</tr>
<tr>
<td></td>
<td>Founder patents as opportunity cost measure (2)</td>
</tr>
<tr>
<td>Log(1 + founder patents)</td>
<td>0.17**</td>
</tr>
<tr>
<td>Log(wages)</td>
<td>0.91***</td>
</tr>
<tr>
<td>(0.26)</td>
<td>(0.31)</td>
</tr>
<tr>
<td>Internet bust years</td>
<td>-0.81***</td>
</tr>
<tr>
<td>(0.30)</td>
<td>(0.34)</td>
</tr>
<tr>
<td>Log(1 + patents)</td>
<td>-0.29***</td>
</tr>
<tr>
<td>(0.09)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>Log(initial scale)</td>
<td>-0.28***</td>
</tr>
<tr>
<td>(0.09)</td>
<td>(0.11)</td>
</tr>
<tr>
<td>Log(1 + patents IT TM)</td>
<td>-0.34***</td>
</tr>
<tr>
<td>(0.10)</td>
<td>(0.20)</td>
</tr>
<tr>
<td>Related start-up</td>
<td>0.03</td>
</tr>
<tr>
<td>(0.08)</td>
<td>(0.37)</td>
</tr>
<tr>
<td>Unrelated start-up</td>
<td>0.03</td>
</tr>
<tr>
<td>(0.05)</td>
<td>(0.30)</td>
</tr>
<tr>
<td>Serial</td>
<td>0.62**</td>
</tr>
<tr>
<td>(0.17)</td>
<td>(0.21)</td>
</tr>
<tr>
<td>Other</td>
<td>0.67</td>
</tr>
<tr>
<td>(0.47)</td>
<td>(0.52)</td>
</tr>
<tr>
<td>No. of founders</td>
<td>-0.16*</td>
</tr>
<tr>
<td>(0.09)</td>
<td>(0.12)</td>
</tr>
<tr>
<td>Constant</td>
<td>-4.77***</td>
</tr>
<tr>
<td>(1.06)</td>
<td>(0.75)</td>
</tr>
<tr>
<td>N</td>
<td>2,117 (249)</td>
</tr>
<tr>
<td>LL</td>
<td>-429.37</td>
</tr>
<tr>
<td>Variance</td>
<td>1.15 (0.94)</td>
</tr>
</tbody>
</table>

Notes. 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 seven submarket dummies.

* Significant at 10%; ** significant at 5%; *** significant at 1%.
failure and cash-out) without being causally linked. Many of the ideas that are exploited by start-ups 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 start-up, 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 start-ups (founder from IT firm)
and unrelated start-ups—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\(^{18}\) 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.

Because 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 cost also yield qualitatively similar results, and direct controls for riskiness leave the coefficient of opportunity cost unaffected.

5.3.3. Fit, Ability to Discern, and Work Experience. As noted in §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 divided by previous year employees) as an additional independent variable.\(^{19}\) The results show that including growth as an additional independent variable diminishes the coefficient of work experience, whereas 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 because 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, start-ups 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 start-up is not the objective.

\(^{18}\)We are grateful to an anonymous reviewer for the suggestion. For five firms we are unable to calculate CV because of missing sizes for one or more years. This leaves us with 244 firms and 2,074 observations in total.

\(^{19}\)For five firms we are unable to calculate employee growth for every year. Moreover because we use growth we also lose one year for every firm. This leaves us with 1,830 observations for this specification.
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 characterizations in ways that obscure the relationship between entrepreneurial characteristics, strategy, and performance. Entrepreneurial opportunity cost is a case in point. Whereas 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.

Acknowledgments
This paper is based on a chapter of Nandkumar’s (2008) Ph.D. dissertation. The paper has improved in response to comments from anonymous reviewers of Management Science. The authors’ names appear in alphabetical order.

Appendix. Proof of Results
1. We first show that the derivation of $V$. Recall that we have two equations:

$$\frac{\partial V}{\partial m} = Pf - \beta V - m = 0 \quad \text{and} \quad V = \frac{m^2/2 + \alpha - mPf}{\beta(1 - m)}.$$  

Substituting for $V$ in the first-order condition, we have

$$\frac{V^2\beta^2}{2} - (1 - \beta(1 - Pf))V - \left(\alpha - \frac{P^2f^2}{2}\right) = 0.$$  

The only feasible solution is

$$V = \frac{1 - \beta(1 - Pf) - A^{1/2}}{\beta^2},$$  

where $A \equiv (1 - \beta(1 - Pf))^2 + 2\beta^2\left(\alpha - \frac{P^2f^2}{2}\right)$.

Using this value of $V$,

$$m^* = 1 - \frac{1}{\beta} + \frac{A^{1/2}}{\beta}.$$  

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

$m^* > 0$ implies $1 - \frac{1}{\beta} + \frac{A^{1/2}}{\beta} > 0$, i.e., $A > (1 - \beta)^2$, and

$m^* \leq 1$ implies $1 - \frac{1}{\beta} + \frac{A^{1/2}}{\beta} \leq 1$, i.e., $A \leq 1$.

3. We now show the condition that ensures $V > 0$. If $V > 0$, we need $\beta^2 - \beta(1 - Pf) > A^{1/2}$ and $J > 1$, which are satisfied for $J$ large enough.

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

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

Because

$$\frac{\partial A}{\partial \alpha} = 2\beta^2,$$

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

5. We show that $\frac{\partial m^*}{\partial Pf} > 0$:

$$\frac{\partial m^*}{\partial Pf} = A^{-1/2} \frac{\partial A}{2\beta} = A^{-1/2}(1 - \beta) > 0.$$  

6. We now show that $\frac{\partial \Omega}{\partial Pf} = m^* + Pf \frac{\partial m^*}{\partial Pf}$.

Because

$$\frac{\partial m^*}{\partial Pf} > 0,$$

$$\frac{\partial \Omega}{\partial Pf} > 0.$$  

7. We now show that the effect of $P$ on $\Omega$ is nonmonotonic:

$$\frac{\partial \Omega}{\partial Pf} = -m^* + (1 - Pf) \frac{\partial m^*}{\partial Pf}.$$  

Because

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

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

Then
\[
\frac{\partial \Omega}{\partial P} > 0 \quad \text{if} \quad (1 - \beta) \left( \frac{1}{\beta} + \frac{J(1-P)}{A^{1/2}} \right) > \frac{A^{1/2}}{\beta}, \quad \text{i.e., when}
\]
\[
(1 - P) > \frac{A^{1/2}}{\beta} \left[ \frac{A^{1/2}}{1 - \beta} - 1 \right], \quad \text{and} \quad \frac{\partial \Omega}{\partial P} < 0 \quad \text{otherwise}.
\]

Thus, for high values of \( P \), \( \Omega \) is decreasing in \( P \), whereas for low values of \( P \), it is increasing in \( P \).

Note that because
\[
A^{1/2} > 1 - \beta, \quad A^{1/2} > 1 - \frac{1}{\beta} > 0.
\]

8. We now show that \( \frac{\partial^2 \Omega}{\partial \alpha \partial P} < 0 \). First,
\[
\frac{\partial^2 \Omega}{\partial \alpha \partial P} = \frac{\beta}{A^{1/2}} - \frac{(1-P)\beta A^{-3/2} \partial A}{\partial P}.
\]

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

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

Also
\[
\frac{\partial^2 \Phi}{\partial \alpha \partial P} = \frac{\partial^2 m^*}{\partial \alpha \partial P} + \frac{\partial P \partial m^*}{\partial \alpha}.
\]

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
\[
\frac{\partial m^*}{\partial P} = J(1-\beta)A^{-1/2}
\]

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

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


CORRECTION

In this article, “Cash-Out or Flameout! Opportunity Cost and Entrepreneurial Strategy: Theory, and Evidence from the Information Security Industry” by Ashish Arora and Anand Nandkumar (first published in Articles in Advance August 4, 2011, Management Science, DOI: 10.1287/mnsc.1110.1381), the fourth displayed equation in section 9 of the appendix was corrected to appear as follows:

$$\frac{\partial^2 \Phi}{\partial \alpha \partial P} = \frac{\partial^2 \mu^*}{\partial \alpha \partial P} - \frac{\partial^2 \Omega}{\partial \alpha \partial P}.$$

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