PULLING THE PLUG: THE CAPABILITY TO TERMINATE UNSUCCESSFUL PROJECTS AND FIRM PERFORMANCE

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Abstract

The recent interest in learning from failure has led to repeated praise of failure as part of the innovation process. The challenges in detecting and terminating failing projects are, however, often underplayed. This study suggests that firms exhibit different propensities to terminate failing innovation projects, and this heterogeneity in part accounts for long-run performance differences between firms in industries with high rates of innovation. An empirical examination of investments in the venture capital (VC) industry shows that VC firms are heterogeneous with respect to their propensities to terminate, and provides evidence that firms with higher termination capabilities have higher performance. In contrast, management of successful projects does not explain performance differences. The findings suggest that, in innovation-intensive contexts where success is rare, the management of failing investments may be at least as important as picking and managing successes, if not more so. The study also investigates the organizational antecedents of a capability to terminate.

Recent years have seen a surge in the interest in learning from failure. Books, blogs and articles provide enthusiastic advice for innovation practitioners to embrace failure in order to achieve success, quoting influential innovators such as Mark Kelley of IDEO, Elon Musk, and Thomas Edison celebrating failure. Academic literature also provides thoughtful accounts of learning from failure, pointing out the challenges and opportunities in managing failures (e.g., Cannon and Edmondson, 2005, Haunschild and Rhee, 2004, Khanna et al., 2016, Madsen and Desai, 2010, Sitkin, 1992).

Missing from many of these accounts is the consideration that detection of failure itself may be a challenge for firms. Many studies focus on exogenous, sudden and visible failures, such as large-scale accidents (e.g., Madsen and Desai, 2010). However, in smaller-scale experiments that are more relevant for innovation, learning first requires a deliberate cessation of the experiment, an admission of failure. This is not always straightforward, as signals are often noisy, ambiguous and even conflicting (Adner and Levinthal, 2004, Knudsen and Levinthal, 2007). Moreover, termination presents a distinct organizational challenge, as it may require severance of relationships and dismantling of assets (Cannon and Edmondson, 2005, Guler, 2007, Zhelyazkov and Gulati, 2016). The ability to terminate such experiments is an important component of learning from failure that is often overlooked. As a recent review of the literature on learning from failure also reveals (Dahlin et al., 2017), an overwhelming majority of studies focus on the processes following failure, and neglect this critical phase of detecting and acting on negative signals to terminate experiments.

The challenges associated with terminating ongoing investments have been well-documented in multiple streams of literature (see Elfenbein and Knott, 2015, Sleesman et al., 2017 for reviews). Less understood is the extent of heterogeneity among decision makers in addressing these difficulties, and the consequences thereof. The objective of this study is to document persistent firm-level heterogeneity in termination policies with respect to failing investments, its antecedents, and performance consequences. Many current explanations of heterogeneity in termination policies focus on rational economic explanations, such as opportunity costs of resources (Gimeno et al., 1997, Lieberman et al., 2017). Another set of studies examines problems of termination as a function of reputation and external ties

(Guler, 2007, Zhelyazkov and Gulati, 2016). The primary argument of this paper is that, controlling for these economic and external explanations, there is still likely to be persistent heterogeneity among firms in termination policies due to cognitive and organizational differences (e.g., Knudsen and Levinthal, 2007). I use the broad term "termination capability" to refer to such heterogeneity, and define it as a firm-level capability to detect and discontinue unsuccessful innovation investments. I use the term "capability" to refer to a heterogeneously distributed firm-level behavior pattern that leads to superior performance (Bloom and Van Reenen, 2007, 2010, Ethiraj et al., 2005, Makadok and Walker, 2000). Termination represents an organizational challenge because the future value of innovative investments is highly uncertain and identifying which investments to terminate requires judgment. In industries where firms make sequential decisions in innovation projects, firms that are able to detect and terminate failures earlier are likely to perform better than others, all else equal.

The empirical study focuses on venture capital (VC) by examining the impact of termination capability (TC) on VC firm performance between 1980 and 2009. VC investments provide an appealing context to study termination for several reasons. First, VC investments carry the typical characteristics of innovation investments under high uncertainty. Ventures receiving VC funding are typically in the early stages of development, with substantial uncertainty about their prospects. The returns to VC investments are highly skewed, and distinguishing between successes and failures early on is a significant challenge. Second, VC firms do not manage the day-to-day innovation tasks, but only engage in the management of a portfolio. This helps isolate portfolio management practices from other innovation-related tasks that could influence terminations. Next, the staged design of VC funding provides firms with opportunities to periodically revisit each decision, and allows researchers to observe sequential decisions to continue or terminate each project in the portfolio. Last, the main objective of VC firms is financial returns, and the concern for understating performance by overlooking other benefits is minimal.

The empirical design mirrors an earlier tradition by inferring persistent firm differences in termination policies by observing the same VC firm across multiple staged investments (Bertrand and Schoar, 2003, Ethiraj and Garg, 2012, Makadok and Walker, 2000). In order to capture firm-specific termination policies, I predict the number of rounds invested in each venture by a given VC over the study period, controlling for the initial match between the ventures and the VCs. I then derive fixed VC firm effects that represent the firm-specific component of termination decisions, controlling for the endogeneity of the match between VCs and ventures. Next, I examine the relationship between this firm-specific termination propensity and firm characteristics, such as expertise and organizational design, controlling for alternative explanations such as opportunity costs. Finally, I examine the impact of these firm-specific termination policies on firm performance.

The received wisdom suggests that the challenge of VC investments lies in picking the few "home run" ventures that generate high returns, while others emphasize that adding value to each venture is key to VC success (e.g., Baum and Silverman, 2004). This study offers a third component of VC performance, namely, termination of failing investments. It suggests that the performance of VC firms depends not only on picking the best investment opportunities, but also on the capability to terminate unsuccessful investments. In fact, since home runs are rare, overall firm performance may have less to do with picking and managing those. Failure is much more common, and identifying and terminating failing investments has the potential to discriminate between high and low performance in the long run. To my knowledge, this is the first study that examines the impact of termination policies on firm performance.

TERMINATION CAPABILITY IN INNOVATION

Part of the challenge of managing innovative projects is that most projects fail while a very small number provides high returns. VC, pharmaceuticals, movies, and publishing are among industries where overall performance depends on the performance of a few hits (Henderson and Cockburn, 1994, Sahlman, 1990, Scherer et al., 2000). Moreover, the long lapse between innovation investments and their outcomes makes it difficult for firms to distill the right lessons from their experience (Levinthal and March, 1993, Lomi et al., 1997). As such, it is almost impossible to predict investment outcomes *ex ante.* Many innovation projects are funded in stages, such that each stage of funding is conditional on meeting milestones set at the prior stage (Cooper, 1990, Klingebiel and Adner, 2015). These projects typically have no intermediate payoffs, and there is uncertainty over the amount and timing of investments that will be required as well as the size of the returns. Decision makers often hold a portfolio of such alternative opportunities competing for resources.

VC epitomizes these characteristics often observed in innovation management. VC firms receive over 60% of returns from about 10% of their investments (Scherer, et al., 2000), while a large proportion of their investments do not break even. They often manage a portfolio of innovative ventures and fund them in stages through multiple financing rounds. The technological and demand uncertainty around a venture is gradually resolved at each round. Theoretical models of VC assume that firms revise their estimated probabilities of success through a Bayesian process as new information becomes available, and continue or terminate investments accordingly (Bergemann and Hege, 1998, Gompers, 1995).

However, recent qualitative and quantitative evidence suggests that VC firms experience substantial difficulty in terminating investments (Guler, 2007, Zhelyazkov and Gulati, 2016). According to Guler (2007), while the likelihood of a successful outcome follows an inverse-U shaped distribution over the number of rounds invested, the likelihood of termination fails to mirror this, illustrating the challenge of termination. VC firms use milestones to measure ventures' interim performance, but milestones only provide an incomplete benchmark, leaving VC firms to rely on subjective assessments. In interviews, venture capitalists stated that termination is "one of the most difficult decisions that venture capitalists face" (Guler, 2007: 258). Moreover, VC firms suffer reputational costs and sanctions from peers when they terminate investments (Guler, 2007, Zhelyazkov and Gulati, 2016). Such challenges make termination decisions far from straightforward. This is somewhat surprising, since VC partners are not engaged in the daily tasks of project management or innovation, and should perhaps find it easier to terminate investments than corporate managers. However, prior work stops short of exploring heterogeneity across firms in their termination capabilities, and its performance consequences.

Heterogeneity of Termination Capability

According to rational economic models, differences in termination policies are due to varying thresholds, since firms may have different alternative uses for the resources released (Gimeno, et al., 1997, Helfat and Eisenhardt, 2004, Lieberman, et al., 2017). These studies implicitly assume that, once these differences are accounted for, firms will be uniform in their abilities to terminate investments. However, if detecting candidates for termination poses a cognitive challenge, firms may also exhibit variations in termination policies due to differences in cognitive capabilities.

The starting assumption of this study is that decision makers have cognitive limitations (Simon, 1955), and can only process limited amounts of information at a given time (Miller, 1956). Given the high uncertainty surrounding innovation investments, managers' cognitions play an important role in determining their investment decisions (Cho and Hambrick, 2006, Eggers and Kaplan, 2009). Different managers may attend to distinct cues in the environment, and interpret similar events in diverging ways (Barr et al., 1992, Ocasio, 1997). These may in turn shape firms' strategic choices, especially when costly investments are needed under uncertainty (Cho and Hambrick, 2006, Eggers and Kaplan, 2009). Some firms demonstrate superior capabilities to forecast future outcomes than others, as their interpretations align better with the external environment (Durand, 2003). While prior research often focuses on the role of superior foresight in developing new products or acquiring resources, such abilities likely also play a role in terminations. Accurate interpretations of environmental cues help managers match their firm's resource allocation processes to the changes in the external environment (Durand, 2003, Eisenhardt and Martin, 2000). This is likely to influence timing of terminating unsuccessful investments, as it does timing of entry (Eggers and Kaplan, 2009). Moreover, a leading theoretical explanation for an inability to terminate failing projects is cognitive, based on managers' ability to make correct inferences (Elfenbein and Knott, 2015, Staw, 1976). While it is often assumed that decision makers are all subject to such biases, recent work suggests that the accuracy of firm judgments may vary (Kaplan, 2011). Persistent heterogeneity in project evaluation is likely to lead to sustained differences in investment policies over time. I therefore expect,

Hypothesis 1 (H1): VC firms will exhibit persistent heterogeneity in their capability to terminate failing investments.

Firm Characteristics and Termination Capability

Next, I turn to a preliminary investigation of the sources of firm-level heterogeneity in the capability to terminate failing investments. I focus on two potential determinants of screening accuracy that could lead to superior termination capability: Organizational design and expertise.

Work and organization design: Variations in work and organization design may cause heterogeneity between firms in terms of decision effectiveness (Csaszar, 2012, Cyert and March, 1963, Knudsen and Levinthal, 2007, Sah and Stiglitz, 1986). Managers' attention and effort are not unlimited resources and are subject to diseconomies (Levinthal and Wu, 2010, March, 1991, Penrose, 1959). The cognitive load that managers bear could then influence how effectively they make termination decisions. Since terminations are consequential and often rely on incomplete data, they require sustained attention rather than routinized decision making. As such, work and organization structures that provide a balanced workload may mitigate a tendency to commit decision errors.

I focus on two aspects of work and organization design that could lead to heterogeneity between firms in how effectively they mitigate such cognitive limitations. The first has to do with work design. It has been noted in prior work that increased workload decreases the effectiveness of decision making and limits creative thinking (Elsbach and Hargadon, 2006). In a typical VC firm, intensity of workload is a function of the number of ventures in a portfolio. VC firms are typically partnerships rather than hierarchical structures, in which each general partner (GP) has primary responsibility for several ventures. GPs reportedly spend about one half of their time monitoring and managing ventures (Barry, 1994, Gorman and Sahlman, 1989, Lerner, 1994, Sapienza and Gupta, 1994). Each new round of financing requires a thorough review of the venture's progress, and a significant commitment GPs' time and effort. GPs who can allocate more attention to each venture may be able to more accurately evaluate each, spotting red flags sooner. In contrast, in firms where GPs are overly burdened, each venture receives less of a GP's effort and attention, and evaluations of the ventures may be less accurate.

Hypothesis 2a (H2a): VC firms with fewer ventures per general partner are likely to have higher termination capability.

Second, specialization and division of labor are important levers that help reduce the adverse effects of an information overload (Cyert and March, 1963, Lawrence and Lorsch, 1967). In a VC firm, while decision making is concentrated at the GP level, division of labor between GPs and support functions could help ease the burden on GPs. For instance, associates gather data about ventures, perform reviews and run analytical models to support decision making; other members of the firm can provide expertise in specialized legal or financial matters related to term sheet preparation and valuation. In the absence of such support, the workload for partners may be even higher, compromising their ability to gather and analyze the data to make good decisions.

Hypothesis 2b (H2b): VC firms with more members in support functions per general partner are likely to have higher termination capability.

Expertise. Prior experience could improve the accuracy of evaluations leading to termination decisions, and facilitate the formation of structures and mechanisms to support accurate evaluations. As managerial decision makers accumulate experience, they may improve their assessments by developing and testing hypotheses about relationships between observable signals and outcomes (Gavetti and Levinthal, 2000, Levitt and March, 1988). Just as experts' mental representations of physics problems differ from those of novices (Chi et al., 1981), VC professionals often talk about "pattern recognition" through accumulated experience as an important skill in evaluating ventures. Experience could also improve firms' ability to act on such signals, as firms accumulate routines that improve on past performance.

While general experience may help improve the capability to terminate failing investments, specialized experience may have an even greater impact. Specialization allows organizational decision makers to allocate attention to the most salient issues (March and Simon, 1958). Generalist firms may have routines that are broadly applicable but not tailored to signals from any one industry, and thus be less attentive to the right cues (Hansen and Haas, 2001, Ocasio, 1997, Simon, 1997). Moreover, complexity in generalists' operations may make it more difficult to draw inferences from past experience (Haunschild and Rhee, 2004, Ingram and Baum, 1997, Levinthal, 1997). In contrast, a focused investment strategy may enable a firm to better comprehend the subtler, industry-specific cues to assess the progress of its investments and terminate at the right time (Baum and Lant, 2003, Sorenson and Stuart, 2001).

VC firms exhibit variation in the extent of industry specialization (Gupta and Sapienza, 1992). Gompers et al. (2009) show that specialist VC firms have higher performance due to better resource allocation across industries and better investment selection within industries, through focused expertise. An in-depth understanding of a narrower set of industries could also aid in termination through setting more realistic milestones and more accurate assessment of venture progress and external signals. VC firms with a more diversified strategy may have to rely more on the venture's internal management for their assessments, who may selectively share information for continued funding (Admati and Pfleiderer, 1994, Bergemann and Hege, 1998).

Hypothesis 3a (H3a). More experienced VC firms are likely to have higher termination capability.

Hypothesis 3b (H3b). Specialist VC firms are likely to have higher termination capability than generalist VC firms.

Termination Capability and Firm Performance

Every portfolio of uncertain investments includes both successes and failures. Common wisdom suggests that success in innovation portfolios depends on being able to pick the "next big thing," the rare idea that generates high returns and compensates for all other investments. However, spotting such outliers may not be indicative of superior forecasting abilities; in fact, the opposite may be true (Denrell and Fang, 2010). This suggests that picking extreme performers may not be the basis of sustained performance in industries characterized by innovation. In contrast, since investment failure is the statistical norm under conditions of high uncertainty, identifying them early on has the potential to discriminate between high and low performance in the long run.

A faster comprehension of which investments are likely to fail is important in several ways. First, superior foresight is a distinct competence that creates economic surplus for firms (Barney, 1991, Makadok and Walker, 2000). Cognitions of competitors may converge as uncertainty is resolved, and any advantages to be gained vis-à-vis competitors due to superior foresight are likely to gradually diminish. Second, since resource commitments to each project also grow over time, diverting resource flows away from unsuccessful investments as early as possible leads to a more effective resource redeployment (Helfat and Eisenhardt, 2004). Moreover, an inability to terminate projects may reduce the amount of experimentation, influencing future returns (Nanda and Rhodes-Kropf, 2013). A capability to terminate unsuccessful investments is therefore likely to be a persistent source of advantage for firms that make staged investments on a regular basis.

Second, once the termination decision is made, the feedback presents a valuable opportunity to learn. Negative feedback not only prompts the firm to increase search, it also changes the direction of search toward exploration (Cyert and March, 1963, Greve, 1998). Firms that are able to internalize a policy of terminating unsuccessful investments can use this capability to develop mindful learning processes (Levinthal and Rerup, 2006), which in turn can enhance the firm's knowledge base and contribute to its future investments (Sitkin, 1992). Along these lines, auto makers learn more from voluntarily initiated recalls than mandatory ones (Haunschild and Rhee, 2004), personal computer firms that remove products from the market tend to have higher rates of new product introductions (Henderson and Stern, 2004), and pharmaceutical firms that engage in frequent and early voluntary patent expirations enjoy increased research quality (Khanna, et al., 2016).

The competitive and learning explanations suggest that a firm's capability to terminate unsuccessful investments may be an important determinant of long-run performance. I therefore predict,

Hypothesis 4a (H4a): Venture capital firms with a higher capability to terminate unsuccessful investments will have higher performance.

An observed relationship between early termination and performance may be misleading if we ignore policies with respect to successful investments. While it is difficult to directly compare the management of successful and unsuccessful investments, it is possible to learn about the discriminating role of terminations by comparing investment policies with respect to each. For instance, if a firm terminates all projects early, it may effectively avoid commission errors but commit more omission errors (by losing out on attractive opportunities.) So does the management of successful investments have a similar impact on performance as the management of unsuccessful ones?

I expect the latter to have a larger impact for the following reasons. First, signals of success are less ambiguous than signals of failure, and it is easier for firms to discern their next set of actions when faced with positive signals (Adner and Levinthal, 2004). For instance, if a venture has successfully achieved its milestones, VC firms will be similar in their decisions to continue investment. However, if the venture has failed in achieving some or even all of its milestones, VC firms may differ on whether to terminate investment, require a pivot, or treat the bad news as a temporary setback and persist. In other words, acting on adverse signals requires more subjective judgment, and may lead to higher heterogeneity in management practices. Conversely, while firms may have varying abilities to find and attract a high-performing venture, they may be more similar in the management of such a venture once it is in the portfolio.

Hypothesis 4b (H4b): The capability to terminate unsuccessful investments is likely to have a higher association with firm performance than a tendency to continue or terminate successful investments.

EMPIRICAL DESIGN

The data set includes data on US-based ventures that received VC funding between 1980 and 2003, excluding private equity and buyout investments, collected from the VentureXpert database. Other data sources included Ritter's IPO database (2006), the Center for Research in Security Prices (CRSP), Securities Data Corporation (SDC), NBER patent database, Recombinant Capital, Galante's Venture Capital and Private Equity Directory, Pratt's Guide to Venture Capital Sources and Preqin.

I focus on lead investors only, since the lead VC often assumes primary responsibility for a venture and is involved in the venture's progress (Hochberg et al., 2007, Sorensen, 2007). As in prior studies, I identify a VC firm as lead if the it was the sole investor present in the first round of venture funding, was present in every round, made the largest dollar investment in the venture, or was a board member in the venture (Gompers, 1995, Hochberg, et al., 2007, Sorensen, 2007). I exclude VC firms that made fewer than three lead investments in the study period (Hochberg, et al., 2007). The final dataset includes investments by 413 VC firms in 4593 ventures. I track each venture until 2009 to observe exits. This provides at least a 5-year window after the last round of financing, which is sufficient to avoid right censoring, since a typical venture takes 5-7 years from founding to exit (Matusik and Fitza, 2012). 1334 ventures have achieved a successful exit through IPO (539 ventures) or acquisition (795 ventures), while 3259 ventures were unsuccessful.

Step 1: Measuring termination capability (TC)

The empirical strategy to measure firm-level TC is to extract firm fixed effects by examining a given VC's investment policies across multiple ventures. This methodology is akin to those used in numerous past studies. For instance, Bertrand and Schoar (2003) have used a similar methodology to estimate fixed top manager effects by examining the style of each top manager across multiple firms. Makadok and Walker (2000) have examined the impact of forecasting capabilities on performance by estimating money market fund managers' unobservable forecasting capabilities across multiple securities. Ethiraj & Garg (2012) used a similar methodology to capture team-level complementarities in excess of individual player effects across NBA games.

In this study, a VC firm's TC is inferred from the number of rounds it has invested in each failing venture. Firms that have invested fewer rounds in failing ventures are likely to have higher TC. Each financing round is a specific decision point at which the VC firm evaluates available data about a venture, and makes a deliberate decision to continue or terminate funding. This measure is calculated for the VC-venture dyad and may differ from the total number of rounds that the venture has received, especially if other VC firms have continued to invest in the venture after the focal VC has terminated investment. The count of rounds in which the VC invested in a venture represents the number of deliberate decisions that the VC has made to commit further to the venture. This is a more precise measure for the purposes of this study than the duration of funding, which could capture passive waiting periods without further commitments, or amount of funding, which does not consider the sequential nature of the process.

It would be ideal to observe the progress of each venture during funding, and evaluate VC firms' investment policies against objective measures of venture progress. Unfortunately, this is not possible with the available data. I therefore infer a venture's progress by observing the eventual outcome. The assumption is that, if a venture has eventually failed, indicators of failure would be available to investing VC firms during financing. While there may be exceptions, we may expect, on average, that failure would not arrive without any indications. I identify a venture as failed if it did not receive any more funding after the last recorded funding date, or achieve an exit through IPO or acquisition by 2009. IPOs are typically the best exit options for VC firms, due to higher returns (Gompers and Lerner, 2000, Hochberg, et al., 2007, Shane and Stuart, 2002). Acquisitions are often second, and present higher variation in returns, since some may just be asset sales. So it is a realistic assumption that ventures without an IPO or acquisition within five or more years of last funding have failed from the VC firm's perspective. Such ventures are either liquidated, or continue to operate without attractive returns to VC firms.

Since limiting the sample to unsuccessful ventures might introduce sample selection bias, I first examine the number of rounds invested in all ventures, regardless of outcome. I then split the sample into two based on outcomes, and repeat the analysis for subsamples of successful and unsuccessful ventures. The methodology is akin to introducing an interaction effect between firm-specific investment policies and venture success (Aiken and West, 1991). Note that the measure has a somewhat different meaning when the venture has reached a successful event. While investing fewer rounds in successful ventures may indicate a VC firm's ability to reach an exit earlier, it could also indicate the VC firm's tendency to prematurely terminate investments in ventures that have become successful afterward. I do not attempt to distinguish between these scenarios, since this is not the focus of the study[1]. For unsuccessful ventures, number of rounds more closely captures a decision to terminate by the VC firm. Unlike successful ventures, it is reasonable to infer that a VC would have been better off investing fewer rounds in unsuccessful ventures.

[1] Distinguishing between the two requires data on the VC firm's share at each round, and its returns on the round that it has made the final investment in the venture. These data are not available.

The dependent variable is the number of financing rounds that a VC firm invests in a venture. It is important to control for the characteristics of ventures, VC-venture dyad, and market conditions to ensure that the VC fixed effects capture the investment policies of VC firms as closely as possible. I refrain from entering VC-specific variables in this stage to let the fixed effects capture all the variance related to the VC firms[2]. The model specification is as follows:

$$ROUNDS_{ij} = EXP(\alpha + \beta_2 C_{jt} + \beta_3 I_{itj} + \beta_4 M_t + U_i + t + \varepsilon_{ij}) \qquad (1)$$

where i and j denote the VC and venture respectively, t denotes the first year in which VC firm i has invested in venture j, $ROUNDS_{ij}$ is the number of rounds that the VC firm i invested in venture j, $\boldsymbol{C_{jt}}$ is the vector of venture-specific controls, $\boldsymbol{I_{ijt}}$ is the vector of investment (dyad)-specific controls, M_t represents IPO market heat as of year t, U_i are the VC firm-specific fixed effects used to calculate TC, and ε_{ij} is the error term. The model also includes year dummies for the first year of investment by VC firm i in venture j. Since the dependent variable is a count, I use Poisson models with robust standard errors (Cameron and Trivedi, 1998).

Fixed firm effects represent the stable, unobserved aspects of each VC firm that affect the number of rounds it invests in unsuccessful ventures, after accounting for observable venture, investment and time-period effects. The sign on the fixed effects is reversed in subsequent analyses so that the measure takes a larger value for firms with higher TC. Since using estimated variables in subsequent regressions can bias the standard errors for the estimated coefficients downward (Maddala, 1983), I weight each value by the inverse of the standard error on the fixed effect (Bertrand and Schoar, 2003)[3]. Thus, each firm's capability to terminate unsuccessful investments was computed as:

$$TC_i = -\frac{U_i}{s.e.(U_i)} \qquad (2)$$

Control Variables. The first set of controls aims to capture the quality of the ventures receiving VC investment. I first control for each venture's progress with the number of patents issued to each venture

[2] In robustness tests, I included VC-specific control variables in this stage. The main results remained similar.
[3] This correction does not change the results of the analyses. I also ran weighted regression models using fixed effects from Stage 1 instead of calculating a TC measure and found similar results.

(e.g., DeCarolis and Deeds, 1999, Shane and Stuart, 2002, Stuart, 2000) and a count of their alliances, by a given financing round (Gulati, 1998, Stuart et al., 1999). Second, I control for the number of VC firms that invested in the venture, since successful ventures are likely to garner more interest from VCs. I also control for the industry in which the venture operates (Gompers and Lerner, 2000) with dummies for industries defined by VentureXpert (biotechnology, communications and media, computer hardware, computer software and services, consumer related, industrial and energy, internet specific, medical/health, semiconductors, and others.)

I then control for several characteristics of the VC-venture pair that might influence funding patterns (Guler, 2007). I control for the match between the VC firm and the venture in terms of their industry domains. I count the VC firm's investments in each industry, and create a dummy variable that equals 1 if the venture operates in the VC firm's industry domain, *i.e.*, the industry in which it invests most frequently. I also control for the geographic proximity of the VC firm to the venture (Sorenson and Stuart, 2001) with a dummy variable that equals 1 if the VC firm and the venture operate in the same state. I control for the dollar amount of financing that the focal VC firm provided to the focal venture and the average duration (in days) that elapsed between financing rounds (Gompers, 1995). Next, since it may be important to distinguish between cases in which the VC firm terminated while other VC firms continued to invest, and those in which the VC firm has stayed on until the final round of financing (Guler, 2007, Zhelyazkov and Gulati, 2016), I include a dummy that equals 1 if the VC's last round is also the final round of financing for the venture. Last, since the stage of investment could affect the number of rounds, I control for investment stage, with dummies for start-up/seed, early stage, expansion, later stage, or other. Finally, in addition to year dummies, I control for IPO market heat, measured as the number of IPO's at year t (e.g., Gompers and Lerner, 2000).

Heckman selection models. It is important to control for endogeneity because ventures are not randomly distributed across VC firms. A selection bias may be at work, such that the observed termination-performance relationship may be because high-performing VC firms get matched with higher quality ventures, and not due to VC firms' investment policies, as hypothesized (Bottazzi et al., 2008, Sorensen, 2007). I follow prior work on VC (Bottazzi, et al., 2008), and implement Heckman (1979) two-stage selection models as a robustness check.

The Stage 1 selection model estimates the likelihood that a venture gets matched with a particular VC from the population of all possible VC-venture pairs. Since the population is very large, I performed the analysis on a random sample of unmatched VC-venture pairs. For each actual VC-venture match, I include ten potential matches in the same year that were not realized (Sorenson and Stuart, 2008). In the selection model, I include VC and venture characteristics that may influence the match (VC centrality, VC's total portfolio alliances and patents, venture' alliances and patents, VC-venture industry and state match [4].) Following prior work, I use the overall availability of funding for ventures in the venture's state as an exogenous variable in Stage 1 (Bottazzi, et al., 2008). The logic is that the overall amount of available VC funding increases competition for the best deals among VC firms, affecting the match between the VC firms and ventures. But investment policies post-selection depend on the characteristics of the VC and venture, not overall funding levels in the region (Bottazzi, et al., 2008, Sorensen, 2007). Stage 2 then estimates the number of rounds that the VC invests in the venture, conditional on having been matched, with an OLS regression.

Step 2: Covariates of TC

In Step 2, I test Hypotheses 2 and 3 by examining the firm characteristics that explain the variation in TC. For this step, I reorganize the data at the VC firm level. This step includes 229 VC firms only, which have fixed effects for both failed and successful ventures[5]. A comparison of samples for Steps 1 and 2 is presented in Table 2. The mean differences between the samples are not significant. Since TC is a fixed effect, each VC appears once. I calculate all variables as sums or averages over the study period. The OLS model specification for Step 3 is:

$$TC_i = \alpha + \beta_1'' VC_i + \varepsilon \qquad (4)$$

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[4] The results are robust to addition of more controls, e.g., VC's past performance.

[5] Fewer VC firms have fixed effects for successful ventures. When I remove this constraint, sample size increases, and the results for H4a are robust, but I cannot test H4b.

where TC_i is termination capability derived from Step 1, $\boldsymbol{VC_{it}}$ is the vector of VC firm-specific covariates averaged over the study period, as detailed below, and ε is an error term.

Since TC is time-invariant, this analysis only captures correlations between average values of the variables of interest and TC. I repeat the analyses with panel data, where the dependent variable is the number of rounds invested by a VC in an unsuccessful venture (similar to Step 1) instead of TC, and add time-varying covariates explained below. Standard errors are clustered by VC firms.

(1) Work and organization design: The first measure is the number of ventures invested relative to the number of VC professionals employed in the VC firm. When each partner has more ventures to manage, their attention will be more divided, resulting in suboptimal continuation or termination decisions. The second is the number of support members in the VC firm relative to the GPs *(pyramid).* This measure captures the support available to VC partners as they make investment decisions. I designated all VC firm members who have the authority to "write a check" (partner, founder, vice president, principal, managing director, chair) as high-level, and all other members (such as analysts, associates and administrative staff) as support [6]. A larger number of support members relative to higher-level members would indicate that VC partners allocate more of their time and attention to decision making.

(2) VC's experience: I measure a VC's experience as the total number of ventures it invested in the study period. I measure each VC's level of specialization with a concentration measure akin to Herfindahl-Hirshman index for investments in the study period (Gompers, et al., 2009):

$$FOCUS_i = \sum\left(\frac{INVij}{INVi}\right)^2 \quad (5)$$

where $FOCUS_i$ is the investment focus of VC firm i, INV_{ij} is the VC firm i's ventures in industry group j, and INV_i is the total number of VC firm i's ventures. This measure takes a higher value when a firm is more specialized. The third measure is the VC's level of experience in its area of specialization,

[6] http://www.askthevc.com/archives/2006/12/what-do-vc-titles-mean.html; http://www.techstars.com/content/blog/partners-principals-associates-analysts-what-job-titles-mean-in-venture-capital-and-how-entrepreneurs-can-navigate-them/; https://www.inc.com/christina-bechhold/decoding-venture-capital-titles.html, last accessed June 25, 2017. The results are robust to variations in categories.

calculated as the maximum of INV_{ij}. In the VC-venture model, these measures are cumulative from 1980 until year *t* (year of first investment by a VC firm in a venture.)

Control variables: An important alternative explanation for the existence of heterogeneity in termination policies is that firms may be facing opportunities of different quality. Availability of alternative opportunities may influence firms' thresholds for termination such that firms with better alternatives may be quicker to cut investment in failing projects, while others with limited alternative uses for fungible resources may stick with investments for longer (Gimeno, et al., 1997, Lieberman, et al., 2017, Sakhartov and Folta, 2014). In order to rule out this alternative explanation, I control for the quality and composition of a VC firm's portfolio. I compute the total number of patents and alliances by all ventures that received funding from the VC firm in the investment period. In the time-varying model, these measures are calculated for all the ventures that are in the VC firm's portfolio in year *t*. In the time-varying model, I also control for fund age in year *t*, since funds with limited time until liquidation may have more limited opportunities for reinvestment.

Another explanation for heterogeneity that has already been explored in the literature is the external constraints on firm decisions. Firm may avoid terminations if they are more likely to suffer reputational consequences. Following prior work, I control for Bonacich's (1987) eigenvector centrality of the VC firm in the U.S. syndicate network (Hochberg, et al., 2007, Podolny, 2001) as well as the number of syndicate partners (Guler, 2007).

I also include a dummy that equals 1 if the investing fund is an early-stage fund (Hochberg, et al., 2007) and dummies for the industry in which the VC is focused. In the time-varying model, I include controls the number of patents and alliances of the venture, VC-venture industry and state match, VC's amount of investment in the venture, a dummy that equals 1 if VC is present in final round, duration of funding in days, and market heat in year *t*. The model also includes dummies for funding stage in year *t*.

Step 3: Measuring the effect of TC on performance

Step 3 tests H4a and H4b by estimating the effect of TC on VC firm performance. The dependent variable is VC portfolio performance, measured as the total count of IPOs divided by the total number of ventures that the VC invested in the study period (Bottazzi, et al., 2008, Hochberg, et al., 2007, Sorensen, 2007). I only consider IPOs as unequivocal successes due to the variation in returns to acquisitions[7], but also report models with the measure recalculated as the sum of the counts of IPOs and acquisitions over the total number of ventures invested. This measure is particularly suited to the analysis since termination of unsuccessful investments frees up resources for other potential "hits", increasing the rate of success. For consistency, I only use investments in which the focal VC was the lead investor in calculating this measure. As an alternative performance measure, I use fund-level internal rates of return (IRR). This variable is available for a small subset of the firms in the sample (n=131)[8]. For VC firms that have multiple funds, I calculate an average IRR variable weighted by the size of each fund[9]. The independent variable of interest is TC, derived from Step 1. The model specification is:

$$P_i = \alpha + \beta_1' TC_i + \beta_2' VC_i + \varepsilon \quad (3)$$

where P_i is the performance of VC firm i (proportion of successful exits or IRR), TC_i reflects termination capability, $\boldsymbol{VC_i}$ is the vector of VC firm-specific covariates, and ε is an error term. Following prior work, I use OLS regression to predict performance (Hochberg, et al., 2007).

Control variables. I closely follow prior models of VC performance (Hochberg, et al., 2007) and control for the average size of the VC's funds in millions of dollars, the number of VC's funds in the period, average centrality of the VC's funds (Hochberg, et al., 2007, Podolny, 2001), count of the VC's funds that specialize in early-stage investments, dummies for firms in California (CA) or Massachusetts (MA), where VC activity is most intense, and a control for average fund inflows to the VC industry in the U.S. in the year that the VC firm raised its fund(s). I also include industry dummies.

RESULTS

Table 1 presents the descriptive statistics and the correlation matrix for Step 1. The average number of rounds invested in each venture is 2.49 with a range of 1-23, suggesting significant variation across VC

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[7] Comprehensive data on acquisition valuations are not available for a sample of this size and time period.
[8] Tests of differences of means does not reveal significant differences between this sample and the Step 1 sample.
[9] Another useful measure of fund performance is Public Market Equivalent, or PME, which takes into account the returns in the public market in the same period. Unfortunately it requires data on all cash inflows and outflows for all funds, which are not publicly available.

firms in the number of rounds invested in each venture. Table 2 presents comparisons of subsamples of successful and failed ventures. Successful ventures receive more rounds on average (3.75 vs. 2.75 rounds for unsuccessful ventures), which suggests that, on average, VC firms are good at distinguishing successful investments. Average investment duration is also longer for successful ventures, consistent with the notion that VCs use financing rounds to monitor investment progress (Gompers, 1995).

Table 3 presents the results of Equation (1), which tests H1. Models 1 and 2 include all ventures. The sample is then split between failed ventures (Models 3 and 4) and successful ventures (Models 5 and 6). In each sample, the first model presents the Poisson regression models with all controls, while the second includes VC firm fixed effects. Models 7 and 8 report the results of Heckman two-stage selection models for the failed sample, with total VC funds available in the venture's state as the exogenous variable. This variable is significant in the selection model. The inverse Mills ratio is significant without firm fixed effects (Model 7), but not significant with firm fixed effects (Model 8).

The fixed firm effects derived from Model 4 were used to derive the TC measure (Equation 2.) The likelihood ratio test rejects the null hypothesis that the firm fixed effects are simultaneously zero ($p<0.005$), providing support for H1. This suggests the presence of persistent firm-level differences in TC. The average TC is 0.610 (higher numbers indicate higher TC), with a standard deviation of 1.560 and a range between -4.31 and 4.83, suggesting high variation in TC.

Table 4 presents the descriptive statistics for Steps 2 and 3, and Table 5 presents the results of the models explaining firm-level variation in TC (H2-H3). Models 1-4 include TC derived from Step 1 as the dependent variable. VIF statistics did not suggest multicollinearity. In Models 5-8, the dependent variable is the number of rounds in failed ventures, the models are at the VC-venture level, and the coefficients are expected to have the opposite sign compared to Models 1-4. H2a predicted that VC firms with fewer ventures per partner would have higher TC. This variable is significant in Models 6 and 8 at 10% level. The ratio of support members to partners is significant at 10% in Models 2-4, and at 1% in Models 6-8, providing support for H2b. H3a and H3b predicted that firms with more experience and specialists would have higher TC. Since Models 1-4 are cross-sectional, Models 7 and 8 present a better test for these hypotheses. Neither overall experience nor specialized experience is significant in these models. Interestingly, VC focus is significant in Models 7 and 8, suggesting that specialist firms may be more effective at terminations.

Step 3 tests H4, which predicted a positive relationship between TC and firm performance. Table 6 shows the results of the models estimating Equation (3) with various VC performance measures: proportion of IPOs to all investments in the VC firm's portfolio (Models 1-3), the proportion of the sum of the counts of IPOs and acquisitions to all investments (Models 4-6), and weighted IRR for VC's funds active during the study period (Models 10-11). Models 7-9 show results with TC derived from Heckman selection models (Table 2, Model 8) with the proportion of IPOs as the dependent variable, and Model 11 shows the results with IRR as the dependent variable. I checked the models for variance inflation factors (VIF) and did not find evidence of multicollinearity. Each set of results shows a positive and significant relationship between TC and VC performance, providing support for H4a. According to Model 1, a one-standard deviation increase in TC is associated with a 1.5% increase in IPO performance. This is a significant increase, given that the average IPO performance is 17.6%. To test H4b, I included a similar TC measure for the subsample of successful ventures. If a VC tends to invest fewer rounds across the board, this variable should also influence performance in a similar manner. However, this variable is not significant in explaining performance, providing support for H4b. This suggests that VC-level variation in investment policies with respect to successful ventures does not lead to significant performance differences in the same way that the policies regarding unsuccessful ventures do.

Robustness Tests

A key alternative explanation for the observed relationships is the variation in the opportunity costs of the resources expended on underperforming investments. When a VC has many other attractive opportunities, its threshold to terminate poorly performing ventures may be lower due to a higher ability to redeploy its resources elsewhere (Gimeno, et al., 1997, Helfat and Eisenhardt, 2004, Lieberman, et al., 2017, Sakhartov and Folta, 2014). The current design controls for this important explanation by including the observable quality of current ventures in a portfolio through alliances and patents as well as the ability to reinvest the resources through fund age (funds closer to the end of their 10-year term have a lower likelihood of finding, managing and exiting a brand new venture successfully.) The interesting result is that heterogeneity across VC firms remains even when the opportunity cost explanation is controlled for. Moreover, some findings provide support in favor of the capability explanation, despite an opposite prediction through an opportunity cost lens. For instance, I find that VCs with fewer ventures per partner are likely to have higher termination capability, even though they have fewer opportunities in their portfolios to redeploy resources from the termination.

Similarly, it could be that specialist firms have lower thresholds for termination since their resources are more valuable in alternative uses (Sakhartov and Folta, 2014). In order to control for this alternative explanation, I created interaction terms between the VC focus variable and opportunity cost controls (number of alliances and patents of the ventures in a VC's portfolio, fund age.) These interactions provided some nuanced support for the opportunity cost explanation, but the heterogeneity among VC firms remained even after these controls. Finally, since capital redeployment could happen at the fund level rather than firm level, I controlled for the quality of other ventures within a fund rather than the overall VC portfolio. The results were robust. Combined, these results suggest that there is more to the variation in terminations than the rational economic considerations of opportunity costs.

An important caveat for the current design is the inability to precisely identify causal relationships. For instance, it could be that the observed relationship between fewer ventures per partner and termination capability is simply because the VCs that terminate more ventures have fewer remaining ventures in their portfolios. Results remained robust when I lagged the dependent variable (number of rounds) by one year. I then estimated the impact of the number of terminated ventures in the prior period on the number of ventures per partner, and the coefficient estimate was not significant. Similarly, having a "home-run" investment in the portfolio may influence the rounds invested in a particular venture and the performance of the VC. In order to control for this possibility, I coded a dummy variable that identified ventures with proceeds at the 90th percentile of the sample and above. The results did not change. These findings provide some assurance about the direction of causality. Even so, the findings of the study can only suggest correlation and should be interpreted as such.

DISCUSSION

The main argument of the study is that there is persistent variation in TC across firms and that this in part accounts for long-run performance differences. The empirical analysis provides robust support for the arguments advanced in this paper. The analysis reveals significant differences across VC firms in the number of rounds that they invest in unsuccessful ventures, even after controlling for selection and opportunity costs. These differences likely capture variation in judgments about the future value of investments, as well as the organizational advantages that enable firms to terminate investments with relative ease. Moreover, TC is significantly related with long-run VC performance. Interestingly, the number of rounds invested in successful companies is not significantly related with performance. If the results were an artifact of a tendency to invest few rounds in all ventures, all termination policies would have similar impact on performance. Instead, a key correlate of VC performance differences is investment policies with respect to failures only.

An examination of the antecedents of TC reveals some interesting results. Contrary to expectations, experience does not have a significant correlation with TC. This could reflect the difficulty of learning from past failures in improving judgment in innovation (Levinthal and March, 1993, Lomi, et al., 1997), or suggest that learning in VC occurs at the individual partner level. At the same time, variables capturing the cognitive load of partners were significantly correlated with TC. A puzzling result is that specialized firms have higher TC, even though the level of their experience does not matter. This suggests that specialization enables accuracy of judgments but through mechanisms other than expertise. It is also possible that specialized firms can pick among substitute investments within a domain; however, significant variation remained even after careful controls for different levels of opportunity costs.

A key contribution of these findings is that studies of learning from failure in innovation must attend to the challenge of detecting and acting on signals of failure as a precursor. Recent focus on experimentation rightly emphasizes the value of running many and early trials improve overall innovation performance (Thomke, 2003). However, in the absence of a termination capability, the cost to learning from failure may be too great to justify experimentation. Interestingly, while the organizational learning literature focuses on different aspects of learning rom failure, it underplays the initial process of recognizing and acting on failure. While several important studies of learning from failure have noted the challenge of detecting failures (Cannon and Edmondson, 2005, Edmondson, 1996), very few studies have systematically examined this key issue.

In a sense, then, many prior findings on learning from failure that report a positive relationship between prior failures and performance perhaps suffer from a selection bias: They only focus on organizations that that are effective in detecting failures and acting on them. This issue may not be relevant in the case of exogenous and catastrophic failures, but in the context of innovations where firms conduct small experiments and make option-like sequential investments, the issue of detecting and terminating failures is paramount in importance (Adner and Levinthal, 2004, Cannon and Edmondson, 2005). In that sense, this study contributes to an important subset of the learning from failure literature that focuses on intelligent failures (Khanna, et al., 2016, Sitkin, 1992).

This study offers other contributions to the broader literature on innovation. First, it highlights the salience of termination for effective staged investment strategies. Prior research reports that firms use a staged investment logic in managing R&D investments (McGrath and Nerkar, 2004), business development options (Folta and Miller, 2002, Kogut and Kulatilaka, 1994), product development (Cooper, 1990), as well as VC or corporate VC portfolios (Gompers, 1995, Hurry et al., 1992). This study provides evidence that simply adopting a staged logic does not guarantee superior outcomes over one-shot investments. The end value of such investments depends critically on firms' termination capabilities.

The study highlights investment termination as a distinct competence in the VC industry as a complement to picking and building ventures (Baum and Silverman, 2004). Unsuccessful investments comprised over two thirds of the total sample (3259 out of 4593 ventures), while only less than 10% of investments became home runs. Therefore, gains associated with superior initial picking may be largely offset if firms cannot manage unsuccessful investments effectively. Moreover, picking good ventures requires luck as well as skill, whereas termination capabilities are relevant for all firms regardless of luck. The conjecture of this study is that the quest for high performance in the VC industry perhaps lies not in successful initial *search under uncertainty* but in successful *management under uncertainty.*

The study underscores an important but often-neglected component of resource allocation in innovative industries broadly characterized by high initial uncertainty and skewed distribution of returns, such as movies, music, pharmaceutical R&D, and new product development. Idiosyncratic characteristics notwithstanding, this study suggests that a *strategy of search* for the outliers should be supported by a *strategy of management* of the run-of-the-mill. Long-run performance perhaps depends less on the ability to generate large abnormal returns, but more on the ability to minimize frequency of normal losses.

This study has several limitations. First, since it is impossible to observe the counterfactuals in this setting, we do not know about ventures that could have been successful if funded. However, given VCs' aggregate tendency to support ventures for as long as possible (Guler, 2007, Zhelyazkov and Gulati, 2016), this concern may be minimal. In addition, the study is based on the premise that the best way to deal with unsuccessful projects is termination. While this assumption excludes situations where ventures can pivot to a previously unforeseen opportunity (McGrath et al., 2004), it is based on the notion that investments and resources have opportunity costs (Adner and Levinthal, 2004, Helfat and Eisenhardt, 2004).

These limitations notwithstanding, the study underlines the importance of termination of investments as a counterpoint to initiating them. It is therefore important to further examine the organizational practices that support effective termination.

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Table 1. Descriptive statistics and correlations for step 1

		1	2	3	4	5	6	7	8	9	10	11
1	VC-venture rounds	1.000										
2	Venture's patents	-0.026	1.000									
3	Venture's alliances	-0.087	0.173	1.000								
4	Venture's VC investors	0.398	-0.006	0.028	1.000							
5	Fund age at investment	-0.068	-0.002	-0.002	0.009	1.000						
6	VC-venture industry match	-0.047	-0.022	-0.012	-0.057	-0.087	1.000					
7	VC-venture in same state	0.002	-0.019	-0.066	0.044	0.019	0.020	1.000				
8	VC-venture inv. amt (log)	0.292	-0.029	-0.001	0.216	0.015	-0.037	-0.063	1.000			
9	VC-venture inv. duration	0.409	-0.025	-0.076	0.247	-0.029	-0.034	0.006	0.168	1.000		
10	VC at final round	-0.080	0.010	-0.024	-0.334	-0.028	0.026	-0.013	-0.056	0.045	1.000	
11	Market heat	0.024	-0.022	0.002	0.018	0.067	-0.004	-0.011	0.200	-0.005	-0.004	1.000
	Mean	2.486	0.813	0.214	3.50	3.87	0.415	0.45	7.49	128.1	0.873	311.3
	S.D.	1.989	17.704	1.181	3.398	5.587	0.493	0.498	1.468	162.9	0.333	153.2

Correlation values greater than 0.028 are significant

Table 2. Comparison of samples

Panel 1 - Ventures	Successful ventures		Failed ventures			
	Mean	Std. dev.	Mean	Std. dev.	t-test: diff>0	P(T>t)
Patents before funding	0.218	2.142	0.14	1.912	1.209	0.113
Alliances before funding	0.109	0.774	0.027	0.005	5.192	0.00
Cumulative patents	1.225	0.215	0.706	0.371	0.871	0.192
Cumulative alliances	0.535	2.006	0.085	0.545	11.776	0.00
Number of rounds invested	3.75	2.898	2.745	2.413	12.056	0.00
VC investors in venture	4.898	4.286	2.997	2.888	17.434	0.00
Dollar amount of VC investment in company	18,970	38,788	9,178	23,684	10.425	0.00
Average duration between rounds (days)	162.705	173.249	119.302	160.361	8.132	0.00
Lead VC - venture in the same industry	0.369	0.482	0.407	0.491	-2.367	0.991
Lead VC - venture in the same state	0.46	0.498	0.439	0.496	1.273	0.101
Panel 2- VC firms	All sample		Termination sample		Performance sample	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Number of ventures	28.718	27.102	26.149	25.454	31.703	27.765
Number of employees	9.641	8.717	8.903	7.574	10.086	8.773
Pyramid	0.433	1.347	0.399	1.234	0.462	0.787
Centrality	29.539	40.881	28.007	40.979	33.666	43.114
VC ventures - alliances	101.578	176.69	86.345	165.053	116.582	187.687
VC ventures - patents	281.259	582.157	245.811	542.95	290.949	568.096
Average rounds	2.536	2.021	2.389	1.932	2.654	2.095
Sample size	413		409		229	

Table 3. Step 1 - Rounds invested

	(1)	(2)	(3)	(4)	(5)	(6)		(7)	(8)
	All sample	All sample	Failed sample	Failed sample	Success sample	Success sample	Stage 1 – selection model	Failed sample	Failed sample
VC-venture industry match	-0.002	-0.029	-0.007	-0.030	0.024	0.014	0.776***	-0.470*	-0.283
	(0.020)	(0.020)	(0.024)	(0.024)	(0.037)	(0.034)	(0.022)	(0.239)	(0.258)
VC-venture state match	0.004	-0.011	0.005	-0.002	0.0232	0.028	0.858***	-0.519*	-0.283
	(0.019)	(0.023)	(0.023)	(0.029)	(0.032)	(0.037)	(0.022)	(0.254)	(0.279)
Venture's patents	-0.001	-0.001	-0.0001	0.0001	-0.010*	-0.005	0.001	-0.0003	0.0004
	(0.002)	(0.001)	(0.0004)	(0.0003)	(0.005)	(0.003)	(0.001)	(0.001)	(0.001)
Venture's alliances	-0.097***	-0.065***	-0.121***	-0.095***	-0.081***	-0.050***	-0.063***	-0.170**	-0.182***
	(0.012)	(0.010)	(0.025)	(0.025)	(0.013)	(0.009)	(0.015)	(0.053)	(0.055)
Number of VCs	0.037***	0.033***	0.047***	0.043***	0.030***	0.023***		0.179***	0.171***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)		(0.010)	(0.010)
VC-venture amount	0.198***	0.243***	0.192***	0.227***	0.227***	0.304***		0.344***	0.438***
	(0.009)	(0.010)	(0.011)	(0.011)	(0.016)	(0.019)		(0.020)	(0.023)
VC-venture duration	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***		0.003***	0.003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)		(0.0002)	(0.0002)
VC at final round	0.074**	0.048+	0.075*	0.078*	0.110*	0.007		0.223*	0.214*
	(0.028)	(0.027)	(0.037)	(0.036)	(0.043)	(0.039)		(0.092)	(0.099)
Market heat	0.096***	0.116***	0.077***	0.104***	0.147***	0.134***	-0.0118	0.098+	0.166**
	(0.014)	(0.016)	(0.015)	(0.017)	(0.024)	(0.035)	(0.0210)	(0.057)	(0.060)
Available VC funding							-0.016***		
							(0.002)		
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investment year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investment stage dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

VC firm dummies	No	Yes	No	Yes	No	Yes		No	Yes
Inverse Mills ratio								-0.749*	-0.398
								(0.376)	(0.409)
Log pseudo-likelihood	-7658.189	-7285.549	-5294.841	-5006.475	-2301.982	-2120.437			
Wald chi-square test								2122.77	3605.82
P>chi sq								0	0
Constant	-7.856***	-9.176***	-6.771***	-8.632***	-11.26***	-10.71***		-7.374+	-12.85**
	(0.905)	(1.105)	(1.015)	(1.167)	(1.569)	(2.309)		(3.983)	(4.242)
Obs.	4593	4593	3259	3259	1334	1334		38875	38875
Robust standard errors in parentheses									
+ p<0.1, * p<0.05, ** p<0.01, *** p<0.001"									

Table 4. Descriptive statistics and correlations for steps 2 and 3

		1	2	3	4	5	6	7	8	9	10	11	12
1	VC IPO performance	1											
2	VC IPO and acq performance	0.444	1										
3	IRR	0.29	0.245	1									
4	Term capability - failed investments	0.109	0.128	0.113	1								
5	Term capability - successful investments	0.255	0.19	0.14	0.312	1							
6	Ventures per partner	0.138	0.167	0.239	-0.043	0.04	1						
7	Pyramid	0.031	0.04	-0.004	0.155	0.16	0.055	1					
8	VC's ventures - number of alliances	0.349	0.255	0.357	0.055	0.118	0.426	-0.05	1				
9	VC's ventures - number of patents	0.319	0.153	0.305	0.097	0.072	0.231	-0.03	0.588	1			
10	VC experience	0.312	0.22	0.346	0.067	0.097	0.277	-0.034	0.809	0.572	1		
11	VC's industry focus	-0.204	-0.096	-0.118	0.053	0.012	-0.25	-0.101	-0.336	-0.285	-0.427	1	
12	Specialized experience	0.198	0.132	0.128	0.105	0.12	0.032	-0.05	0.342	0.297	0.432	0.282	1
13	Number of partners	0.083	0.001	0.104	0.155	0.051	-0.189	0.053	0.373	0.239	0.495	-0.155	0.205
14	VC centrality	0.268	0.024	0.261	0.067	0.042	0.169	-0.177	0.573	0.381	0.618	-0.253	0.358
15	Early stage fund	-0.041	0.048	0.069	-0.051	-0.093	0.082	-0.242	0.353	0.231	0.461	-0.091	0.316
16	Fund size (log)	-0.078	0.023	0.15	0.119	0.061	-0.089	0.142	0.12	0.078	0.174	0.017	0.094
17	Number of funds	0.275	0.226	0.225	0.076	0.107	0.164	-0.017	0.703	0.509	0.859	-0.378	0.356
18	Average fund inflow (log)	-0.56	-0.253	-0.024	0.079	-0.235	-0.22	-0.111	-0.055	-0.041	0.022	0.189	0.04
	Mean	0.176	0.419	8.915	0.509	2.192	13.673	0.469	48.164	135.619	64.869	0.299	6.737
	S.D.	0.115	0.222	17.028	1.562	2.387	19.217	0.679	84.968	307.592	57.893	0.133	7.829

Values larger than 0.18 are significant at 0.05 level.
N=229

		13	14	15	16	17	18
13	Number of partners	1					
14	VC centrality	0.329	1				
15	Early stage fund	0.222	0.338	1			
16	Fund size (log)	0.347	0.127	-0.12	1		
17	Number of funds	0.534	0.471	0.456	0.115	1	
18	Average fund inflow (log)	0.271	0.005	0.181	0.329	0.117	1
	Mean	6.99	21.323	3.031	3.551	6.459	10.81
	S.D.	5.411	24.112	3.117	1.331	4.506	0.991

Table 5. Step 2 - Explaining termination capability

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ventures per partner		0.001	0.001	0.001		0.007+	0.007	0.007+
		(0.007)	(0.007)	(0.007)		(0.004)	(0.005)	(0.004)
Pyramid		0.323+	0.319+	0.325+		-0.061**	-0.063**	-0.062**
		(0.164)	(0.166)	(0.167)		(0.024)	(0.024)	(0.023)
VC experience			0.004				-0.0003	
			(0.003)				(0.001)	
Specialized experience				0.001				0.0002
				(0.002)				(0.001)
VC's industry focus			0.311	0.204			-0.374*	-0.372*
			(1.327)	(1.480)			(0.188)	(0.183)
VC's average inv. duration in venture						0.001***	0.001***	0.001***
						(0.0001)	(0.0001)	(0.0001)
VC's ventures - number of alliances		-0.001	-0.002	-0.001		-0.001	-0.001	-0.001
		(0.002)	(0.002)	(0.002)		(0.001)	(0.001)	(0.001)
VC's ventures - number of patents		0.001*	0.001*	0.001*		-0.00001	-0.00001	-0.00001
		(0.0003)	(0.0003)	(0.0003)		(0.0001)	(0.0001)	(0.0001)
Number of partners	0.032+	0.032	0.025	0.032	-0.005	-0.001	-0.002	-0.002
	(0.018)	(0.020)	(0.022)	(0.020)	(0.005)	(0.005)	(0.005)	(0.005)
VC centrality	0.006	0.008	0.007	0.008	-0.001**	-0.001**	-0.002**	-0.002***
	(0.005)	(0.006)	(0.006)	(0.006)	(0.0004)	(0.0004)	(0.001)	(0.001)
Early stage fund	-0.052	-0.042	-0.056	-0.044	0.072	0.056	0.060	0.061
	(0.036)	(0.037)	(0.039)	(0.038)	(0.043)	(0.041)	(0.041)	(0.041)
Venture's patents					-0.011	-0.009	-0.009	-0.009
					(0.012)	(0.010)	(0.010)	(0.010)
Venture's alliances					-0.120**	-0.086+	-0.086+	-0.086+

					(0.055)	(0.046)	(0.047)	(0.047)
Number of VC investors in venture					0.047***	0.038***	0.038***	0.038***
					(0.007)	(0.006)	(0.006)	(0.006)
Fund age					-0.009***	-0.009**	-0.011**	-0.011***
					(0.003)	(0.003)	(0.004)	(0.003)
VC-venture industry match					-0.020	-0.005	0.010	0.008
					(0.041)	(0.039)	(0.039)	(0.042)
VC-venture in same state					0.022	0.020	0.017	0.018
					(0.040)	(0.038)	(0.038)	(0.038)
Amount VC invested in venture (log)					0.218***	0.177***	0.178***	0.177***
					(0.014)	(0.013)	(0.013)	(0.013)
VC present at venture's final round					0.131*	0.043	0.044	0.043
					(0.052)	(0.051)	(0.051)	(0.051)
Market heat					0.046	0.018	0.010	0.010
					(0.031)	(0.027)	(0.027)	(0.027)
Constant	2.776***	2.821***	2.702*	2.662*	-4.948*	-2.656	-2.060	-2.055
	(0.763)	(0.700)	(1.165)	(1.185)	(2.000)	(1.789)	(1.787)	(1.786)
VC industry focus dummies	Yes	Yes	Yes	Yes				
Company industry dummies					Yes	Yes	Yes	Yes
Investment year dummies					Yes	Yes	Yes	Yes
Investment stage dummies					Yes	Yes	Yes	Yes
Observations	229	229	229	229	1779	1779	1779	1779
R-squared	0.096	0.133	0.137	0.134				
Wald chi-sq					1842.96	2537.82	2628.54	2647.19
P>chi-sq					0.00	0.00	0.00	0.00

Table 6. Step 3 - Performance models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Term. capability – failures	0.010**		0.009*	0.021*		0.019+	0.018**		0.016**	2.685*	4.647*
	(0.004)		(0.004)	(0.009)		(0.010)	(0.006)		(0.0061)	(1.212)	(2.142)
Term. capability – successes		0.004	0.002		0.008	0.004		0.004	0.002		
		(0.003)	(0.003)		(0.006)	(0.007)		(0.003)	(0.003)		
Fund size (logged)	0.006	0.005	0.005	0.020	0.018	0.019	0.006	0.005	0.006	2.044	2.130
	(0.005)	(0.005)	(0.005)	(0.012)	(0.012)	(0.012)	(0.005)	(0.005)	(0.005)	(1.320)	(1.321)
Fund count	0.007***	0.007***	0.007***	0.017***	0.017***	0.017***	0.007***	0.007***	0.007***	0.208	0.180
	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.389)	(0.392)
Early stage investor	-0.006**	-0.006**	-0.006**	0.001	0.0001	0.001	-0.006**	-0.006**	-0.006**	0.303	0.377
	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)	(0.006)	(0.002)	(0.002)	(0.002)	(0.535)	(0.544)
VC Centrality	0.0003	0.0004	0.0003	-0.001+	-0.001	-0.001+	0.0003	0.0004	0.0003	0.100	0.085
	(0.0003)	(0.0003)	(0.0003)	(0.001)	(0.001)	(0.001)	(0.0003)	(0.0003)	(0.0003)	(0.069)	(0.069)
Capital committed to VC	-0.064***	-0.061***	-0.063***	-0.088***	-0.083***	-0.085***	-0.065***	-0.061***	-0.064***	-3.167	-3.632
	(0.007)	(0.008)	(0.007)	(0.019)	(0.019)	(0.019)	(0.007)	(0.008)	(0.007)	(2.719)	(2.775)
California	0.026*	0.030*	0.026*	0.029	0.036	0.029	0.027*	0.030*	0.027*	3.808	3.968
	(0.013)	(0.013)	(0.013)	(0.033)	(0.033)	(0.033)	(0.013)	(0.013)	(0.013)	(3.926)	(3.920)
Massachusetts	0.004	0.011	0.005	-0.016	-0.0004	-0.014	0.006	0.011	0.007	5.217	5.692
	(0.017)	(0.017)	(0.017)	(0.043)	(0.043)	(0.043)	(0.017)	(0.017)	(0.017)	(4.397)	(4.390)
R-squared	0.545`	0.533	0.545	0.189	0.178	0.190	0.551	0.538	0.553	0196	0.219
N	229	229	229	229	229	229	229	229	229	123	123
+ p<0.1, * p<0.05, ** p<0.01 ,*** p<0.001. Standard errors in parentheses											