TOLERANCE FOR FAILURE AND CORPORATE INNOVATION

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Abstract

We examine whether tolerance for failure spurs corporate innovation based on a sample of venture capital (VC) backed IPO firms. We develop a novel measure of VC investors' failure tolerance by examining their tendency to continue investing in a venture conditional on the venture not meeting milestones. We find that IPO firms backed by more failure-tolerant VC investors are significantly more innovative. A rich set of empirical tests shows that this result is not driven by the endogenous matching between failure-tolerant VCs and startups with high ex-ante innovation potentials. Further, we find that the marginal impact of VC failure tolerance on startup innovation varies significantly in the cross section. Being financed by a failure-tolerant VC is much more important for ventures that are subject to high failure risk. Finally, we examine the determinants of the cross-sectional heterogeneity in VC failure tolerance. We find that both capital constraints and career concerns can negatively distort VC failure tolerance. We also show that younger and less experienced VCs are more exposed to these distortions, making them less failure tolerant than more established VCs.

Key words: tolerance for failure, innovation, patents, venture capital, IPO

JEL classification: O31, G24, G34

1. INTRODUCTION

Innovation is vital for the long-run comparative advantage of firms. However, motivating and nurturing innovation remains a challenge for most firms. As Holmstrom (1989) points out, innovation activities involve a high probability of failure, and the innovation process is unpredictable and idiosyncratic with many future contingencies that are impossible to foresee. Holmstrom thus argues that innovation activity requires exceptional tolerance for failure and the standard pay-for-performance incentive scheme is ineffective. Manso (2011) explicitly models the innovation process and the trade-off between exploration of new untested actions and exploitation of well known actions. Manso shows that the optimal contracts that motivate exploration involve a combination of tolerance for failures in the short run and reward for success in the long run.[1]

In this paper we examine whether tolerance for failure indeed spurs corporate innovation. We adopt a novel empirical approach. We start with venture capital (hereafter VC) investors' attitude towards failure and investigate how such attitude affects innovation in VC-backed startup firms. VC-backed startup firms provide an ideal research setting for our study. These firms generally have high innovation potentials and also high failure risk. Therefore, both tolerance for failure and innovation are very relevant for these firms. Further, innovation in entrepreneurial firms has been an important driver of economic growth in the United States. Thus it is important to understand what factors help to spur innovation in startup companies.

We believe that VC investors' tolerance for failure is crucial for the innovation productivity of VC-backed startups. VC investors are active investors and important decision makers in the startup firms they finance. They typically have the final decision power on whether to continue investment or to terminate a project. If VC investors are not tolerant of early failure, then the ventures they finance are likely to be liquidated prematurely upon initial unsatisfactory progress and therefore lose the chance to be innovative. Therefore, VC investors' tolerance for failure can prevent premature liquidation and allow entrepreneurial firms to realize their innovation potentials.

We infer a VC investor's failure tolerance by examining its tendency to continue investing in a project conditional on the project not meeting milestones. A simple model of VC

[1] Recent empirical research testing the implications of Manso (2011) includes Ederer and Manso (2010) that conduct a controlled laboratory experiment and Azoulay, Graff Zivin, and Manso (2011) that exploit key differences across funding streams within the academic life sciences. Both studies provide supporting evidence for Manso's theory.

project termination suggests that a reasonable proxy for a VC's failure tolerance is the VC firm's average investment duration (from the first investment round to the termination of follow-on investments) in its past *failed* projects. The intuition is that the staging of capital infusions in VC investments gives VC investors the option to abandon underperforming projects. Such option is particularly pertinent in projects that eventually fail because these projects may have failed to meet stage targets even before the liquidation decisions are made. If a project does not show progress towards stage targets, then the choice between giving the entrepreneur a second chance by continuing to infuse capital and writing off the project immediately should to some extent reflect a VC investor's attitude towards failure. Other things equal, the longer the VC firm on average waits before terminating funding in underperforming projects, the more tolerant the VC is for early failures in investments.

We then link a VC investor's failure tolerance to IPO firms backed by the VC investor. For each IPO firm, the relevant VC failure tolerance is the VC investor's failure tolerance at the time when the VC investor makes the first-round investment in the IPO firm. This approach is least subject to the reverse causality problem because the failure tolerance measure captures the investing VC investor's attitude towards failure before its very first investment in a startup firm, which is well before the observed innovation activities of the startup firm.

Our main empirical finding is that IPO firms backed by more failure-tolerant VCs are significantly more innovative. They not only produce a larger number of patents but also produce patents with larger impact (measured by the number of citations each patent receives). The results are robust to alternative measures of VC failure tolerance and alternative empirical and econometric specifications.

While the baseline results are consistent with the hypothesis that VC investors' failure tolerance leads to higher ex-post innovation productivity in VC-backed ventures, an alternative interpretation could be that failure-tolerant VCs are in equilibrium matched with projects that have high ex-ante innovation potentials, and high ex-ante potentials lead to high ex-post outcomes. In other words, it is some ex-ante project or VC characteristics rather than VC failure tolerance that drive the main results. To address this identification concern, we do a rich set of analysis.

Our first identification strategy relies on the intuition that both failed and successful projects undertaken by the same VCs during the same time period should share similar ex-ante characteristics. Therefore, we compute the average investment duration in a VC's past *successful* projects as an alternative "VC failure tolerance" measure. If our results are driven by unobservable ex-ante project or VC characteristics rather than VC failure tolerance, then we expect this alternative measure to have a similar predictive power for startup innovation as our failure tolerance measure does. However, this is not what we find, which provides support for our identification of the failure tolerance effect.

Our second identification strategy is to directly control for VC firm characteristics that are known to affect its project selection ability or investment preference. We show that the effect of VC failure tolerance on startup firm innovation cannot be explained away by controlling for the lead VC firm fixed effects, which absorb the time-invariant differences in project selection abilities across lead VC investors, and proxies for the possible time-varying component of VC project selection abilities such as VCs' past investment experiences and expertise.

Our last set of identification tests relies on the cross-sectional heterogeneity in the VC failure tolerance effect. If our failure tolerance measure indeed captures a VC investor's attitude towards failure, then the marginal impact of our measure on innovation reflects how valuable a VC's failure tolerance is for startup innovation and thus should be stronger in ventures *where the failure risk is higher*. However, if our measure instead captures the ex-ante innovation potentials of ventures as under the alternative interpretation that failure-tolerant VCs are endogenously matched with high-potential ventures, then the marginal impact of our measure reflects how likely ex-ante potentials can turn into successful ex-post outcomes and thus should be stronger in ventures *where the failure risk is lower*.

We find that the effect of VC failure tolerance on startup innovation is much stronger when the failure risk is higher and thus failure tolerance is more needed and valued. Being financed by a failure-tolerant VC is much more important for ventures born in recessions, ventures at early development stages, and ventures in industries in which innovation is difficult to achieve (e.g., the drugs industry). These findings provide further support for our empirical proxy of VC failure tolerance and identification of the failure tolerance effect.

Finally, we explore the determinants of the cross-sectional heterogeneity in VC failure tolerance. We identify two frictions − VC capital constraints and career concerns − that can negatively distort VC failure tolerance. We use a large capital infusion from limited partners to the VC firm (that relaxes the VC's capital constraints) to gauge the VC's exposure to capital constraints and use the VC's recent investment success (that reduces the VC's pressure from career concerns) to gauge the VC's exposure to career concerns. We show that younger and less experienced VCs become more failure tolerant after receiving large capital infusions and after achieving some investment success. However, more established VCs' failure tolerance is insensitive to either capital infusions or recent success. These results suggest that younger and less experienced VCs are more exposed to these distortions, making them less failure tolerant than older and more established VCs.

Our paper contributes to a growing empirical literature in corporate finance on innovation. Several recent papers show that the legal system matters for innovation. Acharya and Subramanian (2009) find that a debtor-friendly corporate bankruptcy code encourages innovation. Fan and White (2003) and Armour and Cumming (2008) show that "forgiving" personal bankruptcy laws encourage entrepreneurship. Acharya, Baghai, and Subramanian (2009) document that stringent labor laws spur innovation by providing firms a commitment device not to punish employees for short-run failures. In a similar spirit, Acharya, Baghai, and Subramanian (2010) find that wrongful discharge laws that make it costly for firms to arbitrarily discharge employees foster innovation. These papers show that if the law provides leniency in the case of either personal failure or corporate failure, then we observe more entrepreneurial activities and innovation. The "forgiveness" of the law is to some extent related to the notion of failure tolerance. Our paper contributes to this strand of research by documenting a more direct effect of failure tolerance on corporate innovation.[2]

Our paper also contributes to the literature on VC investors' role in firm value creation. This literature has shown that VC investors' experiences, industry expertise, staged capital infusions, and network positions can all increase the value of VC-backed startup firms (see Gompers 2007 for a survey of this literature, the latest studies include Hochberg, Ljungqvist, and Lu 2007, Sorensen 2007, Bottazzi, Da Rin, and Hellmann 2008, Hochberg 2008, Gompers, Kovner, and Lerner 2009, Puri and Zarutskie 2011, and Tian 2011). In particular, Kortum and Lerner (2000) find that increases in VC activity in an industry lead to significantly more

[2] Other papers have examined the effect of a firm's ownership structure, organizational structure, stock liquidity, and financing choices on corporate innovation (e.g., Atannassov, Nanda, and Seru 2007, Aghion, Van Reenen, and Zingales 2009, Belenzon and Berkovitz 2010, Lerner, Sorensen, and Stromberg 2011, Fang, Tian, and Tice 2011, and Seru 2011).

innovations. Our paper shows that the variation in VCs' tolerance for failure can explain the heterogeneity in the observed innovation productivity of VC-backed firms.

The rest of the paper is organized as follows. Section 2 discusses the empirical measure of VC failure tolerance. Section 3 describes the empirical specification. Section 4 discusses the main results and robustness issues. Section 5 addresses identification issues. Section 6 studies the heterogeneity in VC failure tolerance. Section 7 concludes.

2. MEASURING FAILURE TOLERANCE

2.1 VC Failure Tolerance: A Conceptual Framework

Failure in this study means unsatisfactory progress in the innovation process. Manso (2011) shows tolerance for failure is crucial to motivate innovation, and such tolerance can be reflected in the principal's choice of the termination threshold for a project. A failure-tolerant principal would choose a threshold lower than the ex-post optimal level, and this tends to encourage innovation from the agent. A failure-intolerant principal would choose a threshold higher than the ex-post optimal level, which tends to discourage innovation.

The implication in Manso (2011) can be well applied to the venture investment setting. VC investors are active and powerful investors in a startup company. They have the final decision power on whether to continue investment or to terminate a project. Such power stems from the staging of capital infusions in VC investments (Gompers 1995 and Tian 2011). Staging allows VC investors to gather information and monitor the project progress. It also allows VC investors to maintain the option to abandon underperforming projects. If a project does not show progress towards stage targets after the initial rounds of investments, then the choice between continuing to infuse capital and terminating funding immediately should to some extent reflect a VC's attitude towards failure in the investment process. Put differently, a VC's failure tolerance resides in its power of termination. Thus, in the VC setting Manso's theory implies that the VC's choice of project termination threshold can be a measure of its failure tolerance.

Empirically, we do not directly observe the VC's choice of termination threshold. However, it is straightforward to show that such choice will directly affect the VC's investment duration in a failed project. We present a simple model of the VC's project termination decision to illustrate this point and to motivate our empirical measure of VC failure tolerance.

Suppose that the quality (or NPV) of a project is η, where

$$\eta = \theta + u.$$

The parameter $\theta \geq 0$ is a constant and is the average quality of the projects in the investment pool. The parameter u represents the project-specific quality. We assume that u is normally distributed with zero mean and precision h_u, and the VC investors observe the distribution parameters. When a VC firm starts to invest in a project, its prior estimate of the project quality is simply θ. As the VC firm interacts with the entrepreneur, it learns about the value of u based on a series of performance signals from the investment. Let δ_n be the *n*-th performance signal. Specifically,

$$\delta_n = u + \varepsilon_n,$$

where ε_n is independent of u and also independent of each other. We assume that ε_n is normally distributed with zero mean and precision h_ε.

The VC firm will stop investing in the project when the posterior estimate of the project quality is below certain threshold. Suppose that the threshold for VC-*i* is ϕ^i.We assume $\phi^i < \theta$, i.e., the termination threshold is below the ex-ante project NPV.[3] The VC will terminate the project after receiving the *n*-th signal, where *n* is the smallest integer that satisfies the following condition:

$$\theta + E(u \mid \delta_1, \delta_2, ..., \delta_n) \leq \phi^i \qquad (1)$$

where $\phi^i < \theta$. That is, the termination threshold is below the ex-ante project NPV. The choice of ϕ^i introduces heterogeneity among VCs. According to Manso (2011), VCs with a high ϕ^i are failure-intolerant, and VCs with a low ϕ^i are failure-tolerant. Note that our intention is not to argue which type of VCs is more correct or more rational. All VC investors behave rationally according to their beliefs and preferences. We will explore the determinants of such heterogeneous preferences in project termination in Section 6.

Given the normality and independence assumptions, the expected value of u given a series of performance signals is as follows:

$$E(u \mid \delta_1, \delta_2, ..., \delta_n) = \frac{h_\varepsilon}{h_u + nh_\varepsilon} \sum_{s=1}^{n} \delta_s = \frac{nh_\varepsilon}{h_u + nh_\varepsilon} \bar{\delta}, \qquad (2)$$

[3] For the purpose of our illustration here, we focus on thresholds that are only a function of the posterior mean. But the results can be generalized to the case in which the thresholds are a function of both posterior mean and precision.

where $\bar{\delta}$ is the average of the n signals. If a project is eventually abandoned, the average performance signal $\bar{\delta}$ must be negative. Plugging (2) into (1), VC-i's investment duration in an eventually failed project is the smallest integer n so that

$$n^i \geq \frac{h_u}{h_\varepsilon} \frac{\theta - \phi^i}{(-\bar{\delta}) - (\theta - \phi^i)}. \qquad (3)$$

Equation (3) is the key equation that provides the conceptual foundation for our empirical measure. Everything else equal, the VC's investment duration in an eventually failed project is negatively related to its choice of termination threshold and thus is positively related to its tolerance for failure.[4]

2.2 VC Failure Tolerance: The Empirical Measure

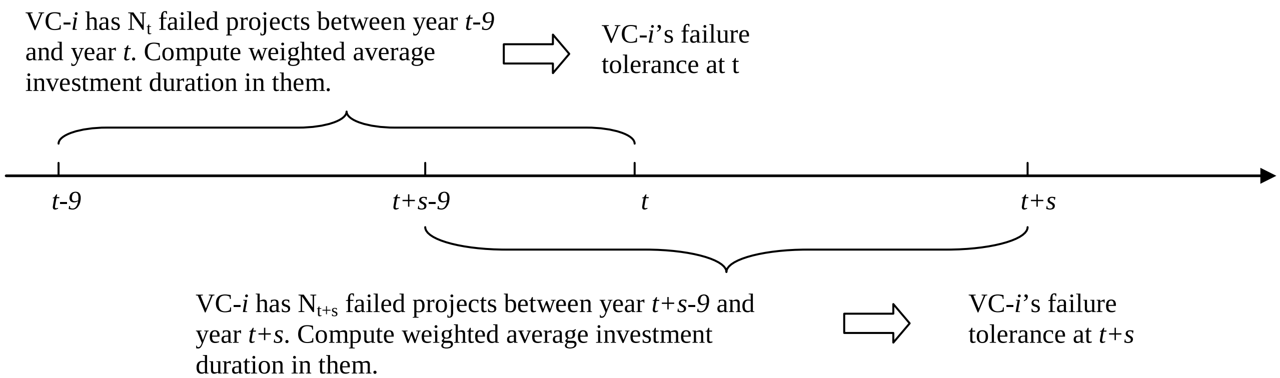
Following the implication of equation (3), we construct the measure of a VC firm's failure tolerance based on the average investment duration in the VC's past failed investments. Specifically, VC firm-i's failure tolerance in year t is the weighted average investment duration in projects that have eventually failed between year t-9 and year t (see Figure 1 for an illustration), where failed projects are those that are eventually written off by their investing VC investors. For robustness, we have also constructed failure tolerance measures using 5-year rolling windows or using the entire cumulative investment history of the VC firm. The investment duration in a project can be described in two ways. One is the time interval (in years) between the first capital infusion from VC firm-i to the termination of funding by VC firm-i. The other is the number of financing rounds the VC firm invests before writing off an underperforming venture. We use the former as the main proxy and the latter as an alternative proxy for robustness checks. The weight for a project is VC firm-i's investment in the project as a fraction of VC firm-i's total investment between year t-9 and year t. Using the average investment duration helps to mitigate the idiosyncrasies of individual projects.

Similarly, VC firm-i's failure tolerance in year t+s is the weighted average investment duration in projects that failed between year t+s-9 and year t+s. Since we use 10-year rolling

[4] It can be shown that $\frac{\partial n^i}{\partial \phi^i} = \frac{h_u}{h_\varepsilon} \frac{\bar{\delta}}{[(-\bar{\delta}) - (\theta - \phi^i)]^2} < 0$. This is because for an eventually failed project, the realized performance signals must be negative on average, i.e., $\bar{\delta} < 0$.

windows to compute the VC's failure tolerance, VC failure tolerance is time-varying, allowing the VC investors' attitude towards failure to slowly change over time.[5]

Figure 1: VC Firm's Failure Tolerance



We obtain data on round-by-round VC investments from the Thomson Venture Economics database for entrepreneurial firms that receive VC financing between 1980 and 2006.[6] Appendix A point A discusses the details of the data cleaning. To construct the VC failure tolerance measure, we focus on VC firms' failed investments, i.e., entrepreneurial firms that are written off by their investing VC investors. Venture Economics provides detailed information on the date and type of the eventual outcome for each entrepreneurial firm (i.e., IPO, acquisition, or write-off). However, the database does not mark all written-down firms as write-offs. Therefore, based on the fact that the VC industry requires investment liquidation within ten years from the inception of the fund in the majority of the cases, in addition to the write-offs marked by Venture

[5] A subtle but relevant concern is whether our measure is capturing a VC's attitude towards risk or attitude towards failure. Tolerance for risk is an investor's *ex-ante* attitude towards uncertainties of investment outcomes, while tolerance for failure reflects how an investor *ex post* reacts to a project's unfavorable outcome. Our measure is more likely to capture a VC investor's tolerance for failure rather than risk for two reasons. First, the venture capital industry is known as the high-risk-high-return industry. Therefore, VC investors are relatively homogenous in their attitude towards risk. Otherwise, they will not invest in the VC industry in the first place. Second, our VC failure tolerance measure is computed based on the VC investor's past failed investments. Therefore, how long a VC investor waits before writing off the project reflects her *ex-post* reaction to an unsuccessful outcome rather than her *ex-ante* willingness to accept high uncertainty in the investment outcomes.

[6] We choose 1980 as the beginning year of our sample period because of the regulatory shift in the U.S. Department of Labor's clarification of the Employee Retirement Income Security Act's "prudent man" rule in 1979. This Act allowed pension funds to invest in venture capital partnerships, leading to a large influx of capital to venture capital funds and a significant change of venture capital investment activities.

Economics, we classify a firm as a written-off firm if it does not receive any financing within a 10-year span after its very last financing round.[7]

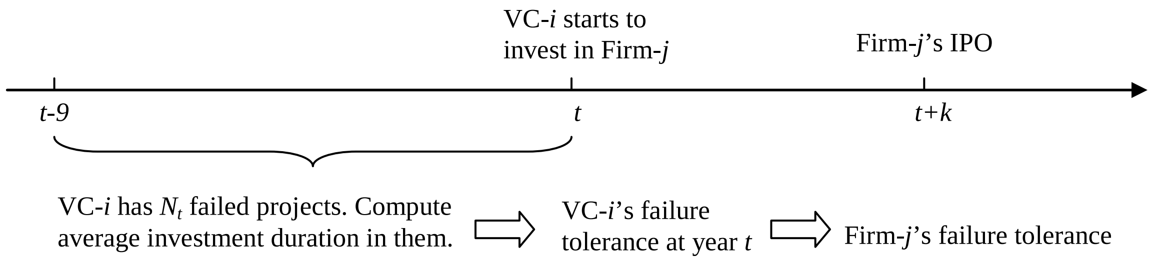
Among all the eventually failed projects, we exclude projects that are in their late/buyout stages when they receive the first-round VC financing. That is, only early-stage ventures that later fail are used to construct the VC failure tolerance measure. Our reason is that late-stage ventures are more mature and the failure risk is significantly reduced. Thus a VC firm's investment duration in these firms may not well reflect its failure tolerance. If a VC firm never invests in any early-stage ventures in our sample, then its failure tolerance would be missing. After further sample cleaning as described in Appendix A point A, we end up with 18,546 eventually failed ventures receiving 67,367 investment rounds from 3,074 VC firms in our sample.

For each failed venture a VC firm has invested in, we calculate the VC firm's investment duration (in years) from its first investment round date to its last participation round date. If the venture continues to receive additional financing from other VC investors after the VC firm's last participation round, then the duration is calculated from the VC firm's first investment round date to the next financing round date after its last participation round. This is because the decision to continue or to terminate funding is generally done at the time of refinancing (Gorman and Sahlman 1989). We then calculate *Failure Tolerance* by taking the weighted average of a VC firm's investment duration in its eventually failed projects up to a given year. We compute the alternative failure tolerance measure based on the number of financing rounds in a similar fashion, and call it *Failure Tolerance 2*. The correlation between the two measures is 0.75.

Now we link the VC's failure tolerance to a future IPO firm financed by the VC. Suppose that the VC firm-i makes its first-round investment in a start-up firm-j in year t, and this firm later goes public in year $t+k$. Then the VC failure tolerance relevant to firm-j is VC firm-i's failure tolerance in year t (see Figure 2 for an illustration). In summary, the relevant VC failure tolerance for an IPO firm is the investing VC firm's failure tolerance at the time when the VC firm makes the first-round investment in the IPO firm.

[7] For robustness, we have also classified a firm as a written-off firm if it does not receive any financing within a 5-year span after its very last financing round. The results are robust to this modification.

Figure 2: IPO Firm's Failure Tolerance



We obtain the list of VC-backed IPOs between 1985 and 2006 from the SDC Global New Issues database.[8] We use the standard exclusions and corrections in the IPO literature (see Appendix A point B). We then merge the IPO sample with our VC firm sample.

For each IPO firm in our sample, we observe the identity of its investing VC firms and the value of each VC firm's failure tolerance measure at their first participation round dates. VC investments are often syndicated (about 91% of our sample), and the lead VC investor usually plays the most important role in monitoring the venture and deciding if a follow-on financing should be made. This implies that the lead VC's attitude towards failure should matter the most to a venture's innovation. Therefore, we choose the lead VC firm's failure tolerance as the main measure for our IPO firms. Following the previous literature (e.g., Hochberg, Ljungqvist, and Lu 2007), we define the lead VC as the one that makes the largest total investment across all rounds of funding in an IPO firm. Alternatively, since all VC syndicate members make investments in the venture, each VC's attitude towards failure may matter. We thus also construct an alternative failure tolerance measure by calculating the weighted average of investing VCs' failure tolerance if an IPO firm receives funding from a VC syndicate. The weight is the investment by a VC firm as a fraction of the total VC investment received by the IPO firm.

Consequently, there are two time-invariant VC failure tolerance measures for each IPO firm in our sample: *Failure Tolerance* is the lead VC's tolerance for failure, and *VC Syndicate Failure Tolerance* is the weighted average failure tolerance of the investing VC syndicate.

Table 1 Panel A reports the descriptive statistics of *Failure Tolerance* and *VC Syndicate Failure Tolerance* by IPO firms. The average lead VC's failure tolerance is about 3.25 years and

[8] We choose 1985 as the beginning year of our IPO sample so that we have a long enough time gap between the beginning year of our VC sample (i.e., 1980) in which the *Failure Tolerance* measure is constructed and the beginning year of our IPO sample in which the *Failure Tolerance* measure is utilized. By doing so, we minimize the possibility that a VC-backed IPO firm has no *Failure Tolerance* information available.

it can be as long as 7.75 years. The average *VC Syndicate Failure Tolerance* is about 2.97 years. This implies that on average the lead VCs are more failure tolerant than other syndicate members.

The distributions of failure tolerance measures are right skewed. Also, from an economic perspective there is a large difference between waiting for two years rather than one year before terminating an investment, but probably a smaller difference between waiting for seven years versus six years. Both the skewness and the likely nonlinearity in the economic impact of VC's tolerance for failure suggest that a logarithm transformation of the failure tolerance measure is appropriate. We then use the natural logarithm of *Failure Tolerance* as the main measure in the rest of the analysis.

3. EMPIRICAL SPECIFICATION

We use "*i*" to denote the lead VC firm, and "*j*" to denote an IPO firm financed by VC-*i*. We use 0 to indicate the time when VC-*i* makes the first-round investment in IPO firm-*j*. Then *t* indicates the *t*-th year after the first-round investment. We generally start to observe innovation outcomes in and after the year of firm-*j*'s IPO. To examine how VC failure tolerance affects startup firms' innovation productivity, we estimate the following baseline empirical model:

$$Ln(Innovation_{j,t}) = \alpha + \beta \times Ln(FailureTolerance^{i}_{j,0}) + \gamma Z_{j,t} + Ind_{j} + Year_{t} + v_{j,t} \qquad (4)$$

The construction of *Innovation* is discussed in detail in Section 3.1. *Z* is a vector of firm and industry characteristics that may affect a firm's innovation productivity. Ind_j and $Year_t$ capture industry fixed effects and fiscal year fixed effects, respectively. A venture's industry membership is based on the 69-industry specifications in the Venture Economics database.

Since VC-*i*'s failure tolerance is time-invariant for IPO firm-*j*, the panel data regression as specified above tends to downwardly bias the estimated effect of failure tolerance. Thus the reported results should be a conservative estimate of the failure tolerance effect. In robustness checks, we use both cross-sectional regressions as well as the Fama-Macbeth regressions, as discussed in detail in Section 4.2.

3.1 Proxies for Innovation

The innovation variables are constructed from the latest version of the National Bureau of Economic Research (NBER) patent database created initially by Hall, Jaffe, and Trajtenberg (2001), which contains updated patent and citation information from 1976 to 2006. The patent database provides annual information regarding patent assignee names, the number of patents, the number of citations received by each patent, the technology class of the patent, the year when a patent application was filed, and the year when the patent was granted. As suggested by the innovation literature (e.g., Griliches, Pakes, and Hall 1987), the application year is more important than the grant year since it is closer to the time of the actual innovation. We therefore construct the innovation variables based on the year when the patent applications are filed. However, the patents appear in the database only after they are granted. Following the innovation literature, we correct for the truncation problems in the NBER patent data (see Appendix A point C).

We construct two measures of innovative productivity. The first measure is the truncation-adjusted patent count for an IPO firm each year. Specifically, this variable counts the number of patent applications filed in a year that are eventually granted. However, a simple count of patents may not distinguish breakthrough innovations from incremental technological discoveries. Therefore, to capture the importance of each patent, we construct the second measure by counting the number of citations each patent receives in subsequent years.

It is true that patenting is a noisy measure of innovation productivity because it is only one of several ways firms use to protect returns from innovations. However, there is no clear reason to believe that such noise, which is in the regression error term in (4), is systematically correlated with the VC failure tolerance measure. Also, we include both industry fixed effects and VC firm fixed effects (in later specifications), which should effectively control for the average differences in the propensity to patent innovation across industries and across VC firms.

We merge the NBER patent data with the VC-backed IPO sample. Following the innovation literature, we set the patent and citation count to be zero for IPO firms that have no patent and citation information available from the NBER dataset. Table 1 Panel B presents the IPO firm-year summary statistics of the innovation variables. On average, an IPO firm has 3.1 granted patents per year and each patent receives 2.5 citations. We also report summary statistics for the subsample of firm-year observations with positive patent counts. This reduces the sample size to 5,264 firm-year observations. The median patent count per year is 3 and the mean is 11.5. On average, each patent receives 9.4 citations.

Since the distribution of patent counts and that of citations per patent are highly right skewed, we use the natural logarithms of patent counts and citations per patent as the main innovation measures in our analysis.[9]

3.2 Control Variables

Following the innovation literature, we control for a vector of firm and industry characteristics (*Z*) that may affect a firm's innovation productivity. In the baseline regressions, *Z* includes firm size (measured by the logarithm of sales), profitability (measured by ROA), growth opportunities (measured by Tobin's Q), investments in intangible assets (measured by R&D expenditures over total assets), capital expenditure, leverage, institutional ownership, firm age (measured by years since IPO), asset tangibility (measured by net PPE scaled by total assets), and industry concentration (measured by the sales Herfindahl index). Detailed variable definitions are in Appendix B.

We extract financial information for the IPO firms from Standard & Poor's COMPUSTAT files and institutional investors' ownership from the Thomson Financial 13f institutional holdings database. All the financial variables in the analysis are winsorized at the 1st and 99th percentiles to mitigate the influence of outliers on the results. Table 1 Panel C reports the summary statistics of IPO firm characteristics. The average IPO firm has sales of $375 million, leverage of 34.64%, net PPE ratio of 17.36%, and Tobin's Q of 3.01.

4. FAILURE TOLERANCE AND CORPORATE INNOVATION

4.1 Baseline Results

Table 2 reports the baseline results on how VC failure tolerance affects a startup firm's innovation productivity. Since both innovation and *Failure Tolerance* are in the logarithm forms, the regression coefficient estimate gives us the elasticity of innovation to *Failure Tolerance*. All regressions include year fixed effects and industry fixed effects. The Huber-White-Sandwich robust standard errors are clustered by IPO firms.

Model (1) of Table 2 shows that IPO firms financed by more failure-tolerant lead VC investors tend to produce more patents. The estimated elasticity of patents to *Failure Tolerance*

[9] To avoid losing firm-year observations with zero patent or patent citation in the logarithm transformation, we add a small number (0.1) to the actual value when calculating the natural logarithm.

is 0.409. This means that a one percent increase in *Failure Tolerance* on average leads to a 0.4 percent increase in the number of patents per year. To be more concrete, consider a VC firm at the 25th percentile of the failure tolerance distribution. According to Table 1 Panel A, this VC firm on average invests for 2.2 years before terminating a project. If this VC firm is willing to invest for 4.3 years before giving up a project (the 75th percentile of the failure tolerance distribution), then holding everything else constant the IPO firms backed by this VC firm tend to have 39% ($= \frac{4.3-2.2}{2.2} * 0.409$) more patents per year later on.

In model (2) we repeat the regression with the main explanatory variable replaced by *VC Syndicate Failure Tolerance*. The VC syndicate's failure tolerance also has a positive and significant impact on the IPO firm's innovation productivity. The estimated elasticity of patents to failure tolerance is 0.343. Not surprisingly, the marginal impact of VC syndicate's failure tolerance on the IPO firm's innovation is smaller than that of the lead VC's failure tolerance. This implies that the lead VC investor's attitudes towards failure matters more for the venture's innovation.

Models (3) and (4) of Table 2 show that firms backed by more failure-tolerant VCs also tend to produce patents with higher impact. Model (3) shows that a one percent increase in the lead VC's failure tolerance on average leads to a 0.35 percent increase in citations per patent. Again, the effect of failure tolerance continues to be present when the VC syndicate failure tolerance measure is used in model (4).

We control for a comprehensive set of firm characteristics that may affect a firm's innovation productivity. We find that firms that are larger (higher sales), more profitable (higher ROA), and have more growth potential (higher *Q*) and lower leverage are more innovative. A larger R&D spending, which can be viewed as a larger innovation input, is associated with more innovation output. Further, higher institutional ownership is associated with more innovation, which is consistent with the findings in Aghion, Van Reenen, and Zingales (2009). Finally, investment in fixed assets (higher capital expenditures), asset tangibility (measured by net PPE over assets) and industry competition (measured by the Herfindahl index) do not significantly impact a firm's innovation productivity.

Overall, our baseline results suggest that a VC's tolerance for failure can increase a startup firm's innovation productivity. These results provide support for the implications of

Holmstrom (1989) and Manso (2011) that tolerance for failure is critical in spurring innovation.

4.2 Robustness

We conduct a set of robustness tests for our baseline results on alternative econometric specifications. Besides the pooled OLS specification reported in Table 2, we use the Fama-MacBeth regression adjusting for auto-correlations of coefficient estimates and get an even stronger estimate for the failure tolerance effect. We also use a Tobit model that takes into consideration the non-negative nature of patent data and citation data. We run a Poisson regression when the dependent variable is the number of patents to take care of the discrete nature of patent counts. We also control for the IPO year fixed effects instead of the fiscal year fixed effects in order to mitigate the effect of strategic IPO timing on our results (Lerner 1994). The baseline results are robust in all the above alternative models, and are thus not reported.

The results are also robust to using alternative ways of measuring failure tolerance. Our main failure tolerance measure is constructed based on the VC's failed projects in the past 10 years. Alternatively, we have used failed projects in the past 5 years or those in the entire investment history of the VC firm since 1980 to construct the failure tolerance measure. The results are very similar. For example, the marginal effect of VC failure tolerance based on 5-year rolling windows is 0.354 (p-value < 0.001) in Table 2 model (1), and it is 0.567 (p-value < 0.001) for failure tolerance based on the cumulative VC investment history. Another alternative measure, *Failure Tolerance 2*, is based on the average number of financing rounds (instead of the number of years) the lead VC investor has made in its past failed projects. The results again hold using this measure. The coefficient estimate for *Ln(Failure Tolerance 2)* in model (1) of Table 2 is 0.269 (p-value = 0.01), and is 0.199 (p-value = 0.02) in model (3).

Focusing on the subsample of firms that have at least one patent in our sample period yields similar results. For example, the coefficient estimate for *Ln(Failure Tolerance)* in model (1) of Table 2 is 0.383 (p-value = 0.005), and is 0.358 (p-value = 0.002) in model (3). This implies that the VC failure tolerance effect is not driven by the large number of firm-year observations with zero innovation count.

The majority of the IPO sample is backed by lead VC investors from California (26%), New York (21%), and Massachusetts (17%). To control for the potential effect of geographic differences on our results, we include a dummy variable for lead VC investors located in each of the three states in the baseline regressions. The estimated failure tolerance effect remains robust. For example, the estimated failure tolerance effect is 0.392 (p-value < 0.001) in model (1) of Table 2, and is 0.340 (p-value < 0.001) in model (3).

Young VCs may not have a long enough history of failed projects and thus the estimate of their failure tolerance can be noisy. As a robustness check, we exclude IPO firms with lead VCs less than five years old from the founding date (about 21% of the IPO sample). Our main results hold. For example, the estimated failure tolerance effect is 0.328 (p-value = 0.008) in model (1) of Table 2, and is 0.289 (p-value = 0.005) in model (3).

In Table 2 we control for industry fixed effects based on the 69-industry classification in the Venture Economics database. Alternatively, we use the 10-industry, 18-industry, and 574-industry specifications in the same database for the industry fixed effects, and the baseline results hold. We have also used two-digit SIC, three-digit SIC, and four-digit SIC, and again the baseline results hold.

We also examine whether the effect of failure tolerance on innovation is monotonic. Is more failure tolerance always associated with higher innovation productivity? In an unreported regression, we replace *Ln(Failure Tolerance)* with *Failure Tolerance* and its squared term. We find that the impact of *Failure Tolerance* on patent counts is positive and significant (coefficient = 0.341, p-value = 0.01), and the coefficient estimate of the squared term is negative and marginally significant (coefficient = -0.030, p-value = 0.09). But such non-monotonicity does not hold for the subsample of firms that have at least one patent in our sample period.

Since the VC's failure tolerance is time-invariant for each IPO firm in our baseline regressions, an alternative way to analyze the data is to run cross-sectional regressions. Thus as our last robustness check, we estimate the VC failure tolerance effect in a cross-sectional regression and report the results in Table 3. The dependent variables are the total number of granted patents that are filed by each IPO firm within the first five years after IPO and the average number of citations each of these patents has received. We impose the arbitrary 5-year threshold to facilitate comparisons of innovation productivity across IPO firms. The independent variable is the lead VC's failure tolerance determined at the time when the VC makes the first-round investment in the venture. The values of all control variables are measured as of the venture's IPO year. Unlike Table 2 where the observation unit is IPO firm-year, the observation unit in Table 3 is IPO firm.

We first include only the lead VC's failure tolerance in Table 3 model (1). The coefficient estimate of *Failure Tolerance* is positive and significant. Also, the cross-sectional variation in VC failure tolerance (along with industry and year fixed effects) explains about 38% of the cross-sectional variation in startup companies' innovation productivity in the first five years after IPO. In model (2), we include all control variables as in Table 2. The coefficient estimate of *Failure Tolerance* continues to be positive and significant. We repeat the regressions in models (3) and (4) with citations per patent as the dependent variables, and find similar results.[10]

5. IDENTIFICATION

Our simple model in Section 2.1 (equation (3)) shows that besides the VC's failure tolerance (ϕ^i), the investment duration in a failed project also depends on project characteristics such as the ex-ante project quality θ and the signal-to-noise ratio h_u / h_ε. Thus the identifying assumption in our baseline regression is that the effect of VC failure tolerance on ex-post startup innovation productivity is not driven by variation in these ex-ante startup characteristics that also influence investment duration in eventually failed projects.

In this section we test our identifying assumption as follows. First, in Section 5.1 we try to understand the nature of the identification problem based on the insights in our simple illustrative model. Then we address the identification problem using three different strategies. In Section 5.2, we construct an alternative measure of "VC failure tolerance" based on the alternative interpretation that it is ex-ante venture characteristics, not VC failure tolerance, that drives our baseline results. We show that this alternative interpretation is not supported by the data. In Section 5.3, we directly control for VC firm characteristics that could affect or reflect its project selection preferences and thus the ex-ante characteristics of its ventures. We find that these VC characteristics cannot explain away our baseline results. Lastly, in Section 5.4, we look for further evidence of identification in the cross section. We slice the sample based on the ventures' ex-ante failure risk. We show that the marginal effect of VC failure tolerance on startup innovation is much stronger in ventures in which the ex-ante failure risk is higher and

[10] In untabulated regressions, we replace the lead VC failure tolerance with *VC Syndicate Failure Tolerance*, and results continue to hold. We also replace separate industry and year fixed effects with industry-year fixed effects to control for possible industry trends in innovation, and the results are robust to such modification.

thus VC's tolerance for failure is more needed and valued. This provides further support for the failure tolerance effect against alternative interpretations.

5.1 What could be the Omitted Variables?

Equation (3) in Section 2.1 shows that besides the VC's termination threshold ϕ^i, the investment duration in a failed project also depends on three other factors. First, the investment duration is increasing in the ex-ante project quality θ, which reflects the average potential of the VC's projects. Second, the investment duration is increasing in the signal-to-noise ratio h_u / h_ε, which reflects the amount of uncertainty and the speed of learning in the investment process. Lastly, the investment duration also depends on the average realized performance signals $\bar{\delta}$, which is a function of the project's idiosyncratic quality u.

In the simple model in Section 2.1 we assume that VC investors are randomly matched with projects in the investment pool with average project quality θ. Now we relax this assumption and assume that different VCs may have different project selection preferences or abilities.[11] Such project selection abilities can be reflected in the average quality of projects undertaken by the VC. Let θ^i be the average quality (or average NPV) of projects undertaken by VC-*i*. Then the quality of a project VC-*i* undertakes is $\eta = \theta^i + u$, where u is still the project-specific quality and is independent of θ^i. Projects undertaken by the same VC are correlated through θ^i, but have independent *u*.

Then it is straightforward to see that θ^i can be an omitted variable in our baseline regression. On the one hand, ventures with higher ex-ante potential θ should on average have higher ex-post innovation productivity. On the other hand, knowing that its projects have a high average quality, VC-*i* is willing to invest in the projects for a longer period of time despite its current underperformance. If VC investors indeed differ in their project selection abilities, then such ability can positively affect both the investment duration in its past failed projects and the innovation productivity of its future successful projects, making our baseline results spurious.[12]

[11] Since we examine equilibrium matching outcomes, the same analysis applies irrespective of whether VCs select projects or projects select VCs. Thus for expositional ease, when we discuss selection ability, we describe it as selection by VC investors.

[12] One possible concern is that our measure of failure tolerance captures a VC's overconfidence. An overconfident VC investor incorrectly thinks that its projects are better-than-average projects, and thus is unwilling to terminate

Next, a high signal-to-noise ratio h_u / h_ε means that the performance signals in the investment process tend to be very noisy (low h_ε). Everything else equal, this implies slow learning and updating for the VC and thus longer investment duration in the venture, no matter what the final investment outcomes are. This ratio may significantly vary across industries. If VCs tend to concentrate their investments in certain industries, then the average signal-to-noise ratio of projects can vary across different VCs. If one believes that more innovative projects tend to have more uncertainty and noisier performance signals, then the signal-to-noise ratio could be an omitted variable as well.

Finally, the investment duration in an eventually failed project also depends on the specific realizations of performance signals about the project's idiosyncratic quality u. However, our model implies that neither u nor $\bar{\delta}$ (the average realized signal of u) introduces an omitted variable problem in the baseline regression. This is because different projects undertaken by the same VC are correlated through θ^i, but have independent u. The u of a past failed project is uncorrelated with the u of a future successful project, and thus has no predictive power for the innovative productivity of future IPOs. Put differently, we do not need to worry about the idiosyncrasies of past failed projects that may affect our VC failure tolerance measure, nor the idiosyncrasies of the future IPO firms that may affect their innovation productivity.

In summary, our simple model of VC project termination suggests that certain ex-ante project or VC characteristics could be the omitted variables in our baseline regression. In particular, the ex-ante project quality, which can be related to VC project selection ability, can introduce a positive relationship between our VC failure tolerance measure and the innovation productivity of ventures. Further, there may be determinants of VC investment duration that are outside our simple model. For example, our model does not incorporate the VC's budget constraints. But the budget situation may influence the VC's decision on when to terminate an underperforming project. Therefore, our task here is to show that the failure tolerance effect we document in the baseline results cannot be explained away after we carefully control for these other determinants of investment duration.

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them despite the underperformance. Such overconfidence certainly leads to longer investment duration in eventually failed projects. However, the ex-post innovation outcome of a future successful project depends on the true quality of the project rather than the perceived quality by the overconfident VC. Thus if a longer investment duration in a failed project is driven by overconfidence, then there is no omitted variable problem. In other words, we do not expect VC overconfidence to systematically predict high innovation outcome in startup firms.

5.2 Investment Duration in Past Successful Projects

To address the identification issues, we wish to control for ex-ante project or VC characteristics that may affect both the investment duration in past failed projects and the ex-post innovation productivity of future successful projects. However, the challenge we face is that many ex-ante project and VC characteristics are not directly observable to researchers.

Our first identification strategy relies on the assumption that the *same* VC's failed investments and successful investments undertaken during the *same* time period should have similar *ex-ante* characteristics, although the ex-post outcomes of these projects are very different. These projects are probably from the same industry, have similar ex-ante risk and return characteristics (as reflected in θ and h_u / h_ε), and reflect similar VC project selection ability, investment style, and budget situation. However, the VC failure tolerance (i.e., the choice of termination threshold for unpromising projects ϕ^i) has a very direct impact on the investment duration of failed projects (as shown in Section 2.1), but much less so on the investment duration of successful projects.

Therefore, the investment duration in the VC's past successful projects provides a nice setting to tease out the effects of some ex-ante project or VC characteristics other than VC failure tolerance on the ex-post venture innovation productivity. If it is the ex-ante project or VC characteristics other than VC failure tolerance that drives our results, then we expect the investment duration of the VC's past successful projects to have a similar predictive power on the ex-post venture innovation productivity as does our failure tolerance measure based on the VC's past failed projects. If, however, our identification assumption holds, then we expect that the investment duration based on past successful projects will have a different effect on startup innovation productivity and cannot explain away our failure tolerance results.

We construct the investment duration in the VC's past successful projects in exactly the same way as we do for our VC failure tolerance measure, and call it "*Duration In Success*". We use 10-year rolling windows and we use only early-stage ventures that later succeed. We then link this variable to the VC's future IPO firms in exactly the same way as we do for the failure tolerance measure. The average lead VC's investment duration in its past successful project is about 3.82 years and it can be as long as 7.43 years. The correlation between the average investment duration in the VC's past successful projects and that in its past failed projects is 0.50. The high correlation implies that these two variables indeed share some common determinants.

In Table 4 we replace VC failure tolerance with the average investment duration in VC's past successful projects in our baseline regressions. In model (1), *Duration In Success* has a positive but insignificant effect on the ventures' patent counts (0.087, p-value = 0.45). In model (2) we add the failure tolerance measure. The effect of *Duration In Success* becomes negative and insignificant (-0.074, p-value = 0.56), while the failure tolerance effect is still positive and significant (0.416, p-value < 0.001). We find similar results for patent citations in models (3) and (4).

The results in Table 4 suggest that ex-ante project or VC characteristics (other than VC's failure tolerance) that affect both the duration of successful projects and that of failed projects cannot explain away the effect of VC failure tolerance on ventures' ex-post innovation productivity.

5.3 VC Firm Fixed Effects and Investment Experience/Preference

Our second identification strategy is to directly control for VC firm characteristics that are observable and known to affect its project selection ability/preference and thus ex-ante project characteristics based on the existing literature.

First, we include lead VC fixed effects in our baseline regression. This helps to control for the effect of any unobservable and time-invariant VC characteristics. For example, if the VC firm's project selection ability or preference, as reflected in the ex-ante project quality and the project signal-to-noise ratio, has a time-invariant component, then including the VC fixed effects helps to mitigate their effects. Note that our empirical measure of VC failure tolerance is time-varying. Thus including VC firm fixed effects gives us the estimate of the within-VC firm failure tolerance effect.

The VC's project selection ability may also exhibit a predictable time trend. A reasonable conjecture is that the VC firm becomes better at selecting projects as it accumulates investment experiences over time. Sorensen (2007) shows that more experienced VCs invest in better projects. Thus we assume that the ex-ante average project quality is $\theta_t^i = \theta^i + \varphi \times EXP_t^i$, where EXP_t^i is VC-*i*'s investment experience and expertise at time *t*. In this case, both the time-invariant θ^i and the time-varying EXP_t^i could be the omitted variables in the baseline regression. We need to explicitly control for both.

In summary, to control for ex-ante project or VC characteristics, we extend our baseline regression to include both lead VC firm fixed effects and lead VC firm time-varying investment experience and expertise. We estimate the following model:

$$Ln(Innovation_{j,t}) = \alpha + \beta Ln(FailureTolerance^{i}_{j,0}) + \varphi EXP^{i}_{j,0} + \theta^{i} + controls + v_{j,t} \quad (5)$$

Both VC-*i*'s failure tolerance and its investment experiences are measured at the time when the VC firm makes the first round investment in the IPO firm-*j*. The parameter θ^{i} represents VC firm fixed effects. The controls are the same as those in the baseline regression.

We measure VC experience from three different angles: past general investment experience, past successful experience, and industry expertise. For each lead VC firm and each year we compute three VC general investment experience measures: a) the total number of firms the VC firm has invested in the past 10 years (*Past No. of Firms Invested*); b) the total dollar amount the VC firm has raised in the past 10 years (*Past Fund Raised*); and c) the age of the VC firm measured as the number of years since its date of inception (*VC Age*). These VC experience measures, especially the past funds raised, can also capture the degree of capital constraint the VC firm faces.

A VC's project selection ability may be best reflected in its past success. The VC literature suggests that going public is the most desirable outcome for both entrepreneurs and VC firms (see, e.g., Sahlman 1990, Brau, Francis, and Kohers 2003). Only firms of the best quality may access the public capital markets through an IPO (Bayar and Chemmanur 2011). Therefore, for each VC firm and each year, we compute *Past IPO Exit* as the proportion of entrepreneurial firms financed by the VC firm that has exited successfully through IPO in the past 10 years.

Another important dimension of a VC firm's experience is its investment specialization. We consider two dimensions of specialization. The first one is the VC's expertise in certain industries. We measure such industry expertise by examining the concentration of a VC's portfolio firms across industries. Following the VC literature, we construct an investment concentration index for each VC firm in each year based on the Venture Economics' industry classification (see details in Appendix B). The measure equals zero if the VC firm's portfolio has exactly the same industry composition as the hypothetical VC market portfolio, and the value of the measure increases as the VC's portfolio becomes more concentrated in a few industries.

Some VC firms specialize in investing in early-stage ventures, and others specialize in later-stage ventures. To capture this dimension of VC investment specialization, we compute the fraction of the VC's investments (both successful and failed) in early-stage ventures in the past 10 years, and call it "*% Investment in Early Ventures*". The Venture Economics database provides information about the development stage of a venture when it receives the first-round VC financing. An early-stage venture is one that receives the first-round VC investment when it is in either the "startup/seed" stage or "early stage" as described in the database.

Table 1 Panel A shows that the average lead VC firm in a given year is about 14 years old, has raised $187 million dollars and invested in 57 entrepreneurial firms in the past 10 years. Among all ventures the average lead VC firm has financed, 24% goes public. [13] The average lead VC's portfolio firms are concentrated in a few industries with the investment concentration index of 0.16. On average, 39% of the lead VC's investments are early-stage ventures.

Table 5 reports the results from the extended empirical model (5). Since the three VC general investment experience variables are highly correlated with each other, we include them one by one in the regressions. We suppress coefficient estimates of control variables to save space. We find that the effect of VC failure tolerance on startup firms' innovation productivity becomes even stronger. The average estimated elasticity of patents to *Failure Tolerance* across the three models is 0.630, and the average estimated elasticity of patent citations to *Failure Tolerance* is 0.413. Further, after controlling for VC failure tolerance, the other VC firm characteristics largely do not affect the innovation productivity of the IPO firms. Only the VC's past IPO exit rate has a marginally positive effect on the number of patents.

In summary, results in Table 5 suggest that controlling for unobservable and time-invariant VC characteristics and time-varying VC investment experiences and expertise cannot explain away the positive VC failure tolerance effect documented in our baseline regressions.

5.4 Identification in the Cross Section

In this section, we rely on the cross-sectional variation in startups' ex-ante failure risk to identify the failure tolerance effect. High failure risk means that given a venture's innovation potential, the probability of achieving a desirable innovation outcome is low. If our failure tolerance measure indeed captures a VC investor's attitude towards failure (ϕ^i) and VC's failure tolerance can help a venture realize its innovation potentials, then we expect the marginal impact

[13] The average IPO exit rate in our sample could be higher than the averages in the entire VC sample. This is because all the lead VCs in our sample have had at least one IPO exit in the sample period. Thus the least successful VCs are not in our sample.

of failure tolerance on innovation to be stronger in firms *where the failure risk is higher*. This is because when the failure risk is higher, tolerance for failure is much more needed and valued for a venture's survival and eventual success.

Under the alternative interpretation, however, the variation in our empirical proxy for failure tolerance largely captures the variation in the average ex-ante quality or innovation potential of VCs' projects (θ^i). Then the marginal impact of this variable on innovation reflects how much the ex-post innovation outcome increases due to an increase in the ex-ante potential of a venture. In other words, the marginal effect reflects how likely ex-ante potentials can be converted into ex-post good outcomes, which is likely to happen when there is little uncertainty in the innovation process, i.e., the failure risk is low. Thus if the alternative interpretation were true, then we expect the marginal effect of the failure tolerance measure on innovation to be stronger in firms *where the failure risk is lower*.

We slice the sample in three different dimensions to capture the cross-sectional differences in startups' failure risk: ventures' "birth" cohorts, development stages, and industries.

5.4.1 Birth Cohort of Venture and the Failure Tolerance Effect

Everything else equal, startup firms that are "born" in a recessionary time period face higher failure risk than those "born" in a booming time period. Uncertain economic outlooks, tight capital supplies, and poor product market demand in recessions all imply that survival is more difficult for startup firms. If our failure tolerance measure indeed captures VC investors' attitude towards failure, then we expect to observe a larger impact of VC failure tolerance on innovation in firms "born" in recessions when the failure risk is higher. If our failure tolerance measure instead captures the average ex-ante quality of ventures, then we expect to observe a larger marginal effect in firms "born" in non-recessionary periods when the failure risk is lower.

Since we want to examine the impact of VC investors, we define a firm's birth cohort based on the time when it receives the first-round VC financing. We create a dummy variable *Recession* that equals one if a venture receives the first-round VC financing in a recessionary period and zero otherwise. The recessionary periods are defined based on the NBER recession dates. The recessions in our sample include the 1980-1982, the 1990-1991, and the 2001-2002 recessions. About 16% of the IPO firms are classified as born in recessions.

We estimate the extended empirical model (5) separately for ventures born in recessions and those not. The results are reported in Table 6. The marginal impact of VC failure tolerance on patent generation for firms born in recessions is 2.215, almost quadruples the impact for firms not born in recessions (0.597). The results are similar for patent impact (1.490 vs. 0.402). The differences across the two groups are also statistically significant. These results suggest that being financed by a failure-tolerant VC is much more important for ventures born in recessions.

One may argue that ventures that are able to obtain VC financing in a recessionary period may have better quality ex ante and thus are more innovative ex post than those obtaining financing in a good time. In other words, being born in a recession proxies for not only higher failure risk but also higher average venture quality. However, even if this argument were true and our *Failure Tolerance* variable captured ex-ante venture quality rather than VC failure tolerance, the alternative interpretation still can not explain the differential marginal effects in the two subsamples in Table 6. This is because having a higher average quality alone does not necessarily imply that the marginal impact of ex-ante quality on ex-post outcome should be higher for this group of firms.

5.4.2 Development Stage of Venture and the Failure Tolerance Effect

The failure risk varies in different stages of an entrepreneurial firm's life cycle. In general, the probability of failure is the highest at the very beginning stages of the firm. As a venture overcomes early difficulties and matures into later development stages, its failure risk reduces. Thus everything else equal, we expect the marginal impact of VC failure tolerance on venture innovation to be stronger for ventures in their early development stages.

The Venture Economics database provides information about the development stage of a venture when it receives the first-round VC financing. We construct an indicator variable *Early Stage* that equals one if a venture is in either the "startup/seed" stage or "early stage" when it receives the first-round VC investment (hereafter early-stage ventures). This indicator variable equals zero if a venture is in "expansion", "later stage", "buyout/acquisition" or "other" stages when it receives the first-round VC financing (hereafter late-stage ventures). About 62% of the IPO firms are classified as early-stage ventures. The average age at the first-round VC financing is 0.53 year (194 days) for the early-stage ventures, and is 7.97 years for the late-stage ventures.

We estimate the extended empirical model (5) separately for early-stage ventures and late-stage ventures. The results are reported in Table 7. The marginal impact of VC failure tolerance on patent generation for early-stage ventures is 0.763 and significant at the 1% confidence level, while it is 0.397 for late-stage ventures and is not significant. The results are similar for patent impact (0.466 vs. 0.055). The differences across the two groups are statistically significant. The results in Table 7 suggest that being financed by a failure-tolerant VC is much more important for early-stage ventures than for late-stage ventures.

Hellmann and Puri (2000) find that innovative firms are more likely to obtain VC financing earlier in the life cycle than do imitators. Thus early-stage ventures may have higher innovation potentials and thus higher ex-post innovation outcome than do late-stage ventures. In other words, the early-stage dummy may proxy for not only high failure risk but also high innovation potential. However, similar to the rationale presented in Section 5.4.1, the argument that early-stage ventures on average have higher ex-ante potential alone has no direct implication that the marginal impact of the VC failure tolerance proxy on innovation should be higher for this group of firms.

5.4.3 Difficulty in Innovation and the Failure Tolerance Effect

If VC failure tolerance is important for startup innovation because innovation activities often involve substantial risk of failure, then a natural cross-sectional implication is that VC failure tolerance should be particularly important in industries in which innovation is difficult to achieve, i.e., failure risk is high. If our failure tolerance measure indeed captures VC investors' attitude towards failure, then we expect to observe a larger impact of failure tolerance on innovation in these industries. If our failure tolerance measure instead captures projects' average ex-ante innovation potential, then we expect to observe a larger marginal effect in industries where failure risk is lower.

Different types of patents involve different degrees of difficulties as well as different levels of rewards. Following the work of Hall, Jaffe, and Trajtemberg (2005), we classify patents in our sample into four categories: (1) drugs, medical instrumentation, and chemicals (hereafter drugs); (2) computers, communications, and electrical (hereafter computers/electrical); (3) software programming and internet applications (hereafter software); (4) other miscellaneous patents (hereafter low-tech).[14] If a firm has no patent, then we classify it into one of the above four categories based on the type of patents that is most frequently produced by the firm's industry.

Common sense suggests that among the above four categories, patents of new drugs are the most difficult to produce. A new drug development process involves many steps requiring different levels of experimentation. Existing studies suggest that the cost of developing a new drug varies from $500 million to $2 billion (see, e.g., Adams and Brantner 2006). On the other hand, developing a new software program may not demand that amount of time and resources and the probability of success may be much higher. Thus we expect tolerance for failure to be more important in industries producing new drugs than industries developing new software programs.

We run the extended empirical model (5) for each industry category separately. Table 8 shows that there is a significant difference in the marginal impact of VC failure tolerance on startup innovation across industries. As expected, the effect of VC failure tolerance on innovation productivity is the strongest in the drugs industry. The estimated elasticity of patents to failure tolerance is 0.771 in the drugs industry, substantially higher than that in the software industry (0.170). The differences in the marginal impact of failure tolerance between the drugs industry and other industries are statistically significant. We find a similar pattern when the effect of failure tolerance on patent impact is examined. These results suggest that being financed by a failure-tolerant VC is much more important for ventures in the drugs industry than for those in the software and low-tech industries.

One potential concern is whether the cross-industry differences in the failure tolerance effect is driven by the cross-industry differences in the propensity to patent innovation. However, firms in the drugs industry actually tend to have fewer patented innovations than do firms in other industries. For example, the average number of patents per year is 2.78 for firms in the

[14] Hall, Jaffe, and Trajtemberg (2005) have six categories: chemicals, drugs and medical instrumentation, computers and communications, electrical, metals and machinery, and miscellaneous. We group chemicals with drugs for two reasons. First, we only have a few observations of chemical patents. Second, both the chemical patents and the drug patents in our sample mainly come from industries with 3-digit SIC 283. Software programming patents (computer-related patents generated by the 3-digit SIC industry 737) belong to the computers and communications category. For finer comparisons between different types of patents, we single out software programming. We then group patents related to computer hardware, communications, and electrics together. Finally, we group metals, machinery and miscellaneous together because we do not have many observations of these patents and label this category as miscellaneous patents.

drugs industry, and is 3.21 for firms in other industries. Also, we have controlled for the VC firm fixed effects, which removes the average differences in patenting propensity across VC firms and should subsume any average differences across industries.

In summary, the cross-sectional analysis in Section 5.4 shows that the marginal impact of VC failure tolerance on startups' ex-post innovation productivity is stronger in ventures where the failure risk is higher and thus VCs' failure tolerance is more needed and valued. These findings provide further support for our empirical proxy of VC failure tolerance and the identification of the failure tolerance effect.

6. HETEROGENEITY IN VC FAILURE TOLERANCE

Our analysis so far shows that startup companies financed by more failure tolerant VCs achieve higher innovation productivity. Meanwhile, Table 1 Panel A shows that there is substantial cross-sectional variation in failure tolerance among the VC firms in our sample. Then the next natural question is why not all VCs tolerate failure, given that VC failure tolerance nurtures innovation.

We hypothesize that certain frictions can prevent a VC from being as failure tolerant as it should be. Specifically, we investigate the effects of two frictions on VC failure tolerance: capital constraints (Section 6.1) and career concerns (Section 6.2). We also hypothesize that different types of VCs have different exposures to these frictions, leading to the cross-sectional heterogeneity in VC failure tolerance.

Since the purpose of the analysis in this section is to understand the heterogeneity in VC failure tolerance, we examine all VC investors covered by the Venture Economics database with non-missing values of failure tolerance in our sample period (1980-2006). Thus the VC sample used in this section is larger than the sample used in the previous analysis where only VC firms serving as lead VC investors in an IPO firm are included (3074 VCs vs. 1860 VCs). We call this larger VC sample the VC universe sample. The average VC failure tolerance in the VC universe sample is about 2.4 years (for *Failure Tolerance*) or 2.7 rounds (for *Failure Tolerance 2*).

6.1 Capital Constraints and Failure Tolerance

Our first hypothesis is that capital constraints can distort VC failure tolerance. Venture limited partnership generally has pre-determined, finite lifetime (typically ten years, although extensions are often allowed), and therefore VC firms are often capital constrained and need to raise follow-on funding from their limited partners (LPs) periodically. Existing studies show that capital constraints and fundraising concerns can significantly distort VCs' investment and going-public decisions in their promising projects (e.g., Gompers 1996, Gompers and Lerner 2000, and Lee and Wahal 2004). These concerns will certainly affect their liquidation decisions in their underperforming projects as well. Tolerating failures in ventures requires VC firms to continue injecting funds into their underperforming ventures. Capital constrained VCs may have limited ability to do so. Therefore, we expect the existence of binding capital constraints to negatively affect a VC's failure tolerance.

Furthermore, Gompers and Lerner (1998) show that older and more experienced VC firms are less capital constrained as they are able to raise funds more easily and raise larger funds than younger and less experienced VCs. Therefore, we expect the effect of capital constraints on VC failure tolerance to be more pronounced for younger and less experienced VCs.

While we do not directly observe the degree to which a VC is capital constrained, we expect the constraint to be relaxed after a large capital infusion from LPs into the VC firm. Therefore, we use a VC's large fundraising event to identify the effect of capital constraints on its failure tolerance. Other things equal, we expect VC failure tolerance to increase in the years following the large capital infusion. We further expect the increase in failure tolerance following the large capital infusion to be more significant for younger and less experienced VCs than for older and more experienced VCs.

To identify a large fundraising event for a VC firm, we first identify the calendar year in which the VC raises the largest amount of funds in the sample period based on each VC's annual fundraising amount obtained from the Venture Economics database. We call this year the VC's "*Fundraising Year*" or event year 0. Then we define year 0 and the subsequent four years as the event window. VCs that did not raise any fund in our sample period are not included in this analysis. The average amount of funds a VC firm raises in a given year is $31 million.

In the baseline analysis reported in Sections 4 and 5 where the effect of VC failure tolerance on its IPO firms' innovation productivity is examined, our main failure tolerance measure is a rolling-window measure of a VC's average investment duration in its eventually failed projects in the past 10 years. While such a 10-year time span helps to mitigate the idiosyncrasies of individual failed projects and is suitable for the baseline analysis, it makes it difficult to attribute any changes in failure tolerance to a fundraising event in this event study setting. For example, a change in the value of VC failure tolerance from year 0 to year 1 reflects the difference between the duration of failed projects in year -9 and that in year 1. Given that year -9 is far away from year 0, such difference is not meaningful for the purpose of our event study analysis. Therefore, to gauge the effect of capital constraints on a VC's failure tolerance in the event analysis, we use an alternative measure of VC failure tolerance that is based on 5-year rolling windows of failed projects.

Figure 3 plots the average VC failure tolerance in each year in the event window. VC failure tolerance steadily increases after the fundraising year, rising from 2.26 years in year 0 to 2.83 years in year 4 (a 25% increase). Note that the failure tolerance measure in this analysis is a 5-year rolling-window measure. Therefore, the 25% increase in the value of VC failure tolerance from year 0 to year 4 indicates that the average duration of newly failed projects between year 1 and year 4 is 25% longer than the average duration of projects failed between year -4 and year -1. The pattern in Figure 3 suggests that after the fundraising year, which presumably relaxes VCs' capital constraints, VCs start to hold onto their underperforming projects for a longer time, leading to a longer duration in projects that fail after year 0 than in those that fail before year 0.

Next, we examine the differential effects of capital constraints on failure tolerance for younger (less experienced) VCs and older (more experienced) VCs. We divide all VC investors in our sample into two groups based on *VC Age* and *Past No. of Firms Invested* at the fundraising year. In year 0 the average *VC Age* is seven and the average *Past No. of Firms Invested* is 21. Thus VCs that are younger than seven at year 0 are called "Young VCs" and those that are seven or older are "Old VCs". VCs that have invested in less than (at least) 21 projects at year 0 are called "Less (More) Experienced VCs."

Figure 4 Panel A plots the average VC failure tolerance in each year for young and old VCs separately. We observe that there is a sharp difference between the failure tolerance pattern for young VCs and that for old VCs. Young VCs' failure tolerance increases rapidly after the large capital infusion, rising from 2.05 years in year 0 to 2.87 years in year 4 (a 40% increase). Old VCs' failure tolerance, however, does not exhibit any significant increase after the large capital infusion. The average failure tolerance for old VCs is 2.62 in year 0 and is 2.79 in year 4. Consistent with our hypothesis, the figure suggests that young VCs' failure tolerance is much more sensitive to capital constraints than is old VCs' failure tolerance. Figure 4 Panel B plots the pattern in VC failure tolerance separately for less experienced VCs and more experienced VCs. The patterns are similar to those in Panel A.

In Table 9 we show that these patterns hold in a multivariate regression framework. The dependent variable is the natural logarithm of VC failure tolerance based on 5-year rolling windows. We create an indicator variable for each event year between year 1 and year 4. In each regression we include all these event-year indicators and use year 0 (the fundraising year) as the omitted event year. Therefore, the estimated coefficient of each event-year indicator reflects the difference in VC failure tolerance between the event year and year 0. We control for the VC's expertise in certain industries (*Industry Concentration*) and in certain development stages of ventures (*% Investment in Early Ventures*), respectively. We also include year fixed effects and industry fixed effects. [15]

Model (1) of Table 9 shows that the estimated coefficients of the event-year indicators are all positive and significant, which indicates that VC failure tolerance is higher in the post-fundraising event years than in the fundraising year. The coefficient estimates are also monotonically increasing in magnitudes, which suggest that the average level of VC failure tolerance is monotonically increasing in the period following the fundraising year. The evidence that a relaxation of capital constraints positively affects VC failure tolerance is consistent with our hypothesis that capital constraints can prevent a VC from being failure tolerant.

Models (2) and (3) show the regression results for young and old VCs, respectively. Comparing the estimated coefficients of event-year indicators in columns (2) and (3), we can see that the increase in VC failure tolerance after the capital infusion is much stronger and more significant for young VCs than for old VCs, consistent with our hypothesis. Models (4) and (5) show similar contrasting patterns between less experienced VCs and more experienced VCs.

One particularly noteworthy point is that it is difficult to attribute the changes in VC failure tolerance reported in Figures 3 and 4 to the changes in VCs' project selection abilities. For example, the projects that eventually fail after year 0 (and therefore contribute to the VC failure tolerance after year 0) are likely to have been selected before year 0. Thus the VCs'

[15] If a VC firm invests in multiple industries in a given year, we choose the industry in which the VC firm invests the largest amount of capital in that year for the industry fixed effect. A VC firm may focus its resources in different industries in different years. Therefore, the industry fixed effects are not subsumed when the VC fixed effects are included.

willingness to hold onto these projects longer after the large fundraising cannot be due to an improvement in the VC's project selection ability after the capital infusion.

Overall, the findings reported in this section support the hypothesis that capital constraints can negatively distort a VC's failure tolerance, and such distortion is more pronounced for younger and less experienced VCs.

6.2 Career Concerns and Failure Tolerance

Our second hypothesis is that career concerns can distort VC failure tolerance. VCs have incentives to establish a track record of success because such a record is crucial for their survival and growth. The literature on managerial career concerns has shown that career concerns can distort the manager's investment decisions (see, e.g., Hirshleifer (1992) for a review).

How do career concerns affect VCs' project termination decisions? The existing theoretical literature provides two opposite predictions. On the one hand, terminating a project may unfavorably reflect the manager's ability. Thus managerial career concerns may lead the manager to delay termination (e.g., Boot 1992). This implies that VCs that have larger career concerns may actually appear to be more failure tolerant than those that have smaller career concerns. On the other hand, career concerns can have opposite implications for project termination decisions if the manager needs to allocate limited resources across different projects. Goel et al. (2004) investigate resource allocation decisions in conglomerates when managers are motivated by career concerns. They theoretically show that career concerns can lead the manager to over-allocate resources to divisions that can visibly and favorably reflect his abilities and under-allocate resources to those that cannot. In our setting, each VC firm manages a portfolio of ventures and needs to allocate its limited resources across ventures. Thus the eagerness to establish a track record of success may incentivize VCs to quickly terminate projects that do not show immediate promise (i.e., under-allocation of resources) so that they can focus their resources on promising ones. This implies that VCs that have larger career concerns would be less failure tolerant than those that have smaller career concerns.

Both implications, though opposite to each other, suggest that career concerns can distort VC failure tolerance. To test the implications of the career concerns hypothesis, we first examine how VC age and experience are related with VC failure tolerance. The intuition is straightforward. Survival is a more immediate challenge for younger and less experienced VCs.

Chevalier and Ellison (1999) find that job termination is more performance-sensitive for younger mutual fund managers. Similarly, younger and less experienced VCs should have larger career concerns and stronger incentive to establish a track record of success. Therefore, comparing VC failure tolerance based on VC age and experience helps us understand the effect of career concerns on a VC's failure tolerance.

Figure 4 shows that the level of failure tolerance is on average higher for older and more experienced VCs than for younger and less experienced VCs in the fundraising event window. In Table 10 Panel A we formally examine the relationship between VC failure tolerance and VC age and investment experience. We control for the VC's expertise in certain industries (*Industry Concentration*) and in certain development stages of ventures (*% Investment in Early Ventures*). We also control for the year fixed effects and industry fixed effects. Models (1) and (2) show that the coefficient estimates of VC experience measures (*VC Age* and *Past No. of Firms Invested*) are both positive and significant at the 1% confidence level. The results are robust to controlling for VC fixed effects in models (3) and (4). These findings suggest that younger and less experienced VCs are less failure tolerant than older and more experienced, which is consistent with the hypothesis that career concerns negatively distort a VC's failure tolerance.

In our next test, we use a VC's recent successful investment experience to further identify the effect of career concerns on VC failure tolerance. The intuition is as follows. While we may not directly observe the amount of pressure due to career concerns a VC faces, we believe that such pressure should be relieved to some extent after the VC establishes some record of success in the recent past. In other words, having some recent success serves as a proxy for a *decrease* in VC career concerns. Therefore, if career concerns negatively (positively) affect a VC's failure tolerance, then we expect the VC's failure tolerance to increase (decrease) following recent success. Further, the effect of recent success on failure tolerance should be more pronounced for younger VCs than for older VCs because recent success has a larger positive impact on younger VCs' survival and growth. In other words, we expect the effect of recent success on VC failure tolerance to be more pronounced for younger and less experienced VCs.

To test this implication, we first use the definitions specified in Section 6.1 to define young and old VCs based on *VC Age*, and less and more experienced VCs based on *Past No. of Firms Invested*. Then we construct an indicator variable "*Recently Successful*" for the full sample, for young and less experienced VCs, and for old and more experienced VCs separately based on different criteria for success. For the full sample, *Recently Successful* equals one if the VC's *Past IPO Exit* is greater than 15% (i.e., the median value of *Past IPO Exit* for all VCs), and zero otherwise. For young and less experienced VCs, *Recently Successful* equals one if the *Past IPO Exit* is greater than 8% (i.e., the median value of *Past IPO Exit* for young VCs), and zero otherwise. For old and more experienced VCs, *Recently Successful* equals one if the VC's *Past IPO Exit* is greater than 18% (i.e., the median value of *Past IPO Exit* for old VCs), and zero otherwise. Note that we use different criteria to define success across young and old VCs. This is because having one or two IPOs in the recent past is impressive for a young VC with a short investment history, but is much less so for a well established VC.

In Table 10 Panel B we examine the sensitivity of a VC's failure tolerance to its recent success. Model (1) is estimated for the full sample. The coefficient estimate of *Recently Successful* is positive and significant at the 1% confidence level, suggesting that recent investment success tends to increase a VC's failure tolerant. This result is consistent with the findings reported in Table 10 Panel A that career concerns negatively distort VC failure tolerance. We then further examine how career concerns distort VC failure tolerance differently for young versus old VCs and for less experienced versus more experienced VCs. Model (2) is estimated for young VCs only. Again, the coefficient estimate of *Recently Successful* is positive and significant. This suggests that young VCs that have recently achieved some investment success are significantly more failure tolerant than young VCs that have not. Model (3) shows, however, that recent success has no impact on old VCs' failure tolerance. Old VCs that are relatively successful in the recent past are no more failure tolerant than those that are relatively unsuccessful. This evidence suggests that young VCs' failure tolerance is more sensitive to recent success than is old VCs' failure tolerance. In models (4) and (5) we estimate the same model separately for less experienced VCs and for more experienced VCs. The results are very similar to those in models (2) and (3). These results again support the hypothesis that career concerns can negatively distort VC failure tolerance, and such distortion is more pronounced for younger and less experienced VCs.

A valid concern in the above analysis is that recent success may relax a younger or less experienced VC's capital constraints rather than its career concerns, and thus it is the relaxation of capital constraints that drives our results in Table 10 Panel B. If this argument were true, then less experienced but recently successful VCs should be less capital constrained than less experienced and unsuccessful VCs. Therefore, the failure tolerance of the former should be less sensitive to a large capital infusion than that of the latter. To address this concern, in Figure 5 we plot the patterns of VC failure tolerance in the event window for three groups of VCs: more experienced VCs, less experienced but successful VCs, and less experienced and unsuccessful VCs. We observe that, unlike the failure tolerance of experienced VCs that is insensitive to the large capital infusion, the failure tolerance of less experienced VCs increases rapidly after a large capital infusion, regardless of their recent success. More importantly, less experienced but successful VCs have a similar sensitivity to the large capital infusion as less experienced and unsuccessful VCs do. Thus, the patterns in Figure 5 suggest that the results in Table 10 Panel B are unlikely to be driven by a relaxation of capital constraints due to recent success.

6.3 Other Determinants

Besides the variation in exposures to frictions, we find that other VC characteristics can also explain part of the cross-sectional heterogeneity in VC failure tolerance. Tables 9 and 10 show that the VC's investment expertise (preferences) affects its failure tolerance. VCs whose investments are more diversified across industries are generally more failure tolerant than those whose investments are focused in fewer industries. A possible explanation for this result is that diversification reduces the negative impact of individual project failure on a VC's total portfolio performance, and therefore allows the VC to be more failure tolerant. VCs specializing in early-stage ventures also tend to be more failure tolerant than those specializing in later-stage ventures. This result is intuitive because early-stage ventures are on average more likely to fail and thus VCs investing in these ventures need to be more failure tolerant.

Lastly, Table 10 Panel A shows that VC fixed effects, which represent unobservable time-invariant VC characteristics, can explain a significant portion of the variation in VC failure tolerance. This result suggests that failure tolerance has a fairly stable component. A potential unobservable and fairly stable VC characteristic that may influence VC failure tolerance is a VC firm's corporate culture.

In summary, in Section 6 we investigate the cross-sectional heterogeneity in VC failure tolerance. We find that the existence of two frictions help explain why VCs are not equally failure tolerant. First, capital constraints can negatively distort VC failure tolerance. Younger and less experienced VCs are more likely to face binding capital constraints, and therefore they tend to be less failure tolerant and their failure tolerance is more sensitive to large capital infusions that relax their constraints. Second, career concerns can negatively distort VC failure tolerance. Younger and less experienced VCs are more eager to establish a track record of success, which can make them less failure tolerant. Their failure tolerance is also more sensitive to recent investment success that reduces their career concerns. Finally, certain stable VC preferences and attributes can also help explain the cross-sectional heterogeneity in VC failure tolerance.

7. CONCLUSION

Economic theories suggest that tolerance for failure is crucial for motivating and nurturing innovation. In this paper, we adopt a novel empirical approach to test this implication. We develop a measure of a VC investor's tolerance for failure based on the average investment duration in the VC investor's past failed projects. We find that IPO firms financed by more failure-tolerant VC investors exhibit significantly higher innovation productivity. A rich set of empirical tests shows that this result is not driven by the endogenous matching between failure-tolerant VCs and startups with high ex-ante innovation potentials. Further, the analysis suggests that being financed by a failure-tolerant VC is particularly important for ventures subject to high failure risk. VCs' tolerance for failure allows these startups to overcome early difficulties and realize their innovation potentials.

To understand the determinants of the cross-sectional heterogeneity in VC failure tolerance, we show that both capital constraints and career concerns can negatively distort VC failure tolerance. We also find that younger and less experienced VCs tend to be more exposed to these distortions, making them less failure tolerant than more established VCs. Specifically, younger and less experienced VCs become more failure tolerant after a relaxation of capital constraints and after a decrease in career concerns.

Our study generates some interesting questions for future research. A natural follow-up question from our study is how much VC firms themselves benefit from their tolerance for failure in startup companies. Do more failure-tolerant VCs enjoy higher investment returns? Is the profit-maximizing level of failure tolerance for a VC firm consistent with the socially optimal level of failure tolerance? Since carried interest awarded to the general partner of a VC fund is essentially a call option on the project being financed, does the compensation scheme of VCs affect their failure tolerance? Can alternative compensation structure be designed to induce VCs to be more failure tolerant? Since managers of corporate venture capital (CVC) funds are typically compensated by a fixed salary and corporate bonuses, do CVCs have different failure tolerance levels from traditional VCs? Future research that explores these questions would shed new light on VC failure tolerance and on how to motivate and nurture innovation in startup companies.

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Appendix A: Details in Sample Selection

A. Cleaning the investment round data from Venture Economics:

From the initial set of 282,752 VC investment round observations, we exclude startup firms that are in their late/buyout stages when they receive the first-round VC financing. This is because these firms are more mature and the failure risk is significantly reduced, and thus a VC firm's investment duration in these firms may not well reflect its failure tolerance. We also exclude investment rounds obtained by financial firms, utilities firms and those with missing or inconsistent data. For example, some firms' first VC financing round dates occur before the founding dates of their investing VC firms, and some firms' founding dates occur later than their IPO dates. We also correct for the Venture Economics' over-reporting problem. Gompers and Lerner (2004) document that the database reports 28% more financing rounds than actually occurred because Thomson frequently splits financing rounds. To correct this over-reporting problem, we collect financial information from IPO prospectuses and S-1 registration statements for firms that eventually go public. For firms acquired by public firms, we collect financial information from the acquirers' proxy, 10-K, or 10-Q statements, which are generally available in the SEC's EDGAR database. For firms that are written off or remain private, we eliminate repeated rounds within three months if they share the same amount of round financing.

In the end we have 228,805 individual financing rounds made by 7,384 distinct VC firms in 46,875 distinct entrepreneurial firms.

B. Cleaning the VC-backed IPO data from SDC Global New Issues database:

Following the IPO literature, we exclude from our initial IPO sample spin-offs, closed-end fund, REITs, ADRs, unit offerings, reverse LBOs, foreign issues, offerings in which the offer price is less than $5, finance (SIC code between 6000 and 6999), and utilities (SIC code between 4900 and 4999). We also exclude firms with missing identities of their investing VC firms. We corrected for mistakes and typos in the SDC database following Jay Ritter's "Corrections to Security Data Company's IPO database" (http://bear.cba.ufl.edu/ritter/ipodata.htm).

C. Correcting for truncations in the NBER patent database:

Since there is a significant lag between patent applications and patent grants (about two year on average), the patent database is subject to two types of truncation problems. The first one is regarding patent counts. As we approach the last few years for which there are patent data available (e.g., 2005 and 2006 in the data used here), we observe a smaller number of patent applications that are eventually granted. This is because many patent applications filed during these years are still under review and had not been granted until 2006. Following Hall, Jaffe, and Trajtenberg (2001, 2005), we correct for the truncation bias in patent counts using the "weight factors" computed from the application-grant empirical distribution. The second type of truncation problem is regarding the citation counts. This is because patents keep receiving citations over a long period of time, but we observe at best only the citations received up to 2006. Following Hall, Jaffe, and Trajtenberg (2001, 2005), the truncation in citation counts is corrected by estimating the shape of the citation-lag distribution.

Appendix B: Variable Definitions and Data Sources

Failure Tolerance, VC Characteristics, and Project Characteristics (data source: Venture Economics)	
Failure Tolerance$_{it}$	The average number of years VC firm *i* has invested in its projects that eventually failed in the past 10 years (from year *t-9* to year *t*)
Failure Tolerance 2$_{it}$	The average number of financing rounds VC firm *i* has invested in its projects that eventually failed in the past 10 years (from year *t-9* to year *t*)
Past No. of Firms Invested$_{it}$	The total number of firms VC firm *i* has invested in the past 10 years (from *t-9* to *t*)
Past Fund Raised$_{it}$	The total dollar amount raised by VC firm *i* in the past 10 years (from *t-9* to *t*)
VC Age$_{it}$	Age of VC firm *i* in year *t* measured as the number of years since its year of inception
Investment Concentration$_{it}$	The value for VC firm *i* in year *t* is the sum of the squared deviations of the weights (the number of portfolio firms) for each of the 18 different industries held by the VC firm *i* relative to the industry weights of the total venture investment. Suppose that in year *t* VC firm-*i* has $w_{i,t,j}$ portfolio firms in industry *j* (scaled by the total number of venture firms from year *t-9* to year *t*). There are a total of $\overline{w}_{t,j}$ venture firms in industry *j* (also scaled by the total number of venture firms from year *t-9* to year *t*). The investment concentration of VC firm-*i* at year *t* is defined as the sum of the squared deviations of $w_{i,t,j}$ relative to $\overline{w}_{t,j}$: $\sum_{j=1}^{18}(w_{i,t,j}-\overline{w}_{t,j})^2$.
Past IPO Exit$_{it}$	The proportion of entrepreneurial firms financed by VC firm *i* that goes public in the past 10 years (from year *t-9* to year *t*)
% Investment in Early Ventures $_{it}$	The fraction of the VC's investments (both successful and failed) in early-stage ventures in the past 10 years (from year *t-9* to year *t*). An early-stage venture is one that is in the "startup/seed" or "early stage" when it receives the 1st round VC financing
Annual Fund Raised$_{it}$	The total dollar amount raised by VC firm *i* in year *t*
Innovation Variables (data source: NBER Patent Data)	
Patents$_{it}$	Number of patents firm *i* applies for in year *t*. Only patents that are later granted are included. The variable is also corrected for the truncation bias as detailed in Appendix A point C
Citations/Patent $_{it}$	The average number of citations per patent of firm *i* applies for in year *t*
IPO Firm Characteristics (data source: COMPUSTAT)	
Sales $_{it}$	Sales by firm *i* in year *t* (in $million)
ROA $_{it}$	Operating income before depreciation to total assets ratio of firm *i* in year *t*
R&D/Assets $_{it}$	Research and Development expenditure to total assets ratio of firm *i* in year *t*
CapExp/Assets $_{it}$	Capital expenditure to total assets ratio of firm *i* in year *t*
Leverage $_{it}$	Total debt of firm *i* in year *t* divided by its total assets
Tobin's Q $_{it}$	Market to book ratio of firm *i* in year *t*: (total assets + year end closing price*year end outstanding shares - book equity)/total assets
Institutional Ownership $_{it}$	Total percentage of firm *i*'s equity held by institutional investors in year *t* (Source: Thomson Financial 13f institutional holdings database)
Firm Age $_{it}$	Age of firm *i* in year *t* since its IPO
PPE/Asset $_{it}$	Net property, plants and equipments to assets ratio of firm *i* in year *t*
Herfindahl Index $_{it}$	Herfindahl index of firm *i*'s industry in year *t* constructed based on sales at 4-digit SIC industries

Table 1: Summary Statistics

Panel A: VC Failure Tolerance and Other VC Characteristics

Except for "VC Syndicate Failure Tolerance" and "VC Syndicate Failure Tolerance 2", all other variables are characteristics of the lead VC.

Variable	25%	Median	Mean	75%	S. D.	N
Failure Tolerance	2.19	3.19	3.25	4.26	1.49	1,860
VC Syndicate Failure Tolerance	2.34	2.96	2.97	3.58	1.04	1,848
Failure Tolerance 2	2.37	3.51	3.78	4.91	1.81	1,860
Duration In Success	2.75	3.85	3.82	4.83	1.51	1,751
Past No. of Firms Invested	15	42	57	94	48.56	1,860
Past Fund Raised (mil.)	0.00	49.70	187.19	226.90	347.27	1,849
VC Age	6	12	14.25	21	9.94	1,855
Investment Concentration	0.02	0.05	0.16	0.23	0.22	1,860
Past IPO Exit	0.14	0.21	0.24	0.28	0.18	1,860
% Investment in Early Ventures	0.28	0.38	0.39	0.48	0.21	1,860

Panel B: Innovation

Variable	25%	Median	Mean	75%	Std. Dev.	N
Full Sample						
Patents	0	0	3.11	1	23.71	19,437
Citations/Patent	0	0	2.54	0	11.56	19,437
Sub-sample with patents > 0						
Patents	1.04	3	11.48	7.25	44.51	5,264
Citations/Patent	0	2.55	9.39	8.91	20.72	5,264

Panel C: Control Variables

Variable	Mean	Median	Std. Dev.	N
Sales (mil.)	375.07	51.77	2122.73	16,653
ROA (%)	-10.43	3.81	42.17	16,521
R&D/Assets (%)	14.06	6.98	21.12	19,437
CapExp/Assets (%)	6.15	4.00	6.70	16,371
Leverage (%)	34.64	25.80	34.83	19,437
Tobin's Q	3.01	2.08	2.94	14,230
Institutional Ownership (%)	37.58	32.31	29.01	13,061
Firm Age	2.91	2.00	5.11	19,437
PPE/Assets (%)	17.36	11.19	17.46	16,670
Herfindahl Index	0.24	0.11	0.31	19,437

Table 2: Failure Tolerance and Corporate Innovation

The dependent variable is the natural logarithm of the number of patents in a year in models (1) and (2), and is the natural logarithm of the number of citations per patent in a year in models (3) and (4). The observation unit in this analysis is IPO firm-year. The Huber-White-Sandwich robust standard errors (in parentheses) are clustered by IPO firm. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

	Ln(Patents)		Ln(Citations/Patent)	
	(1)	(2)	(3)	(4)
Ln(Failure Tolerance)	0.409***		0.346***	
	(0.095)		(0.079)	
Ln(VC Syndicate Failure Tolerance)		0.343***		0.317***
		(0.129)		(0.098)
Ln(Sales)	0.101***	0.100***	0.034**	0.033**
	(0.021)	(0.021)	(0.014)	(0.015)
ROA	0.491***	0.507***	0.304**	0.316**
	(0.149)	(0.151)	(0.134)	(0.134)
R&D/Assets	1.437***	1.470***	1.176***	1.201***
	(0.303)	(0.301)	(0.262)	(0.261)
CapExp/Assets	0.825	0.884	0.383	0.429
	(0.660)	(0.659)	(0.655)	(0.654)
Leverage	-0.837***	-0.837***	-0.798***	-0.798***
	(0.184)	(0.184)	(0.139)	(0.140)
Tobin's Q	0.103***	0.103***	0.077***	0.077***
	(0.016)	(0.015)	(0.013)	(0.013)
Institutional Ownership	1.043***	1.074***	0.898***	0.923***
	(0.208)	(0.208)	(0.157)	(0.157)
Firm Age	0.048**	0.047**	0.009	0.007
	(0.020)	(0.020)	(0.011)	(0.011)
PPE/Assets	-0.423	-0.425	-0.436	-0.435
	(0.389)	(0.392)	(0.324)	(0.327)
Herfindahl Index	-0.022	-0.031	-0.064	-0.071
	(0.194)	(0.192)	(0.157)	(0.154)
Constant	-7.470***	-6.988***	-5.590***	-5.178***
	(0.946)	(0.931)	(0.814)	(0.752)
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	11,239	11,239	11,239	11,239
R^2	0.303	0.300	0.249	0.247

Table 3: Cross-Sectional Analysis of the Failure Tolerance Effect

The dependent variable in models (1) and (2) is the natural logarithm of the total number of granted patents that are filed within the first five years after a firm's IPO. The dependent variable in models (3) and (4) is the natural logarithm of citations per patent for granted patents that are filed within the first five years after a firm's IPO. The observation unit in this analysis is IPO firm. The Huber-White-Sandwich robust standard errors (in parentheses) are clustered by lead VC firm. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

	Ln(Total Patents)		Ln(Total Citations/Total Patents)	
	(1)	(2)	(3)	(4)
Ln(Failure Tolerance)	0.686***	0.624***	1.170***	1.068***
	(0.109)	(0.113)	(0.188)	(0.183)
Ln(Sales)		0.043*		0.012
		(0.024)		(0.029)
ROA		0.583		0.267
		(0.400)		(0.493)
R&D/Assets		2.459***		1.912*
		(0.839)		(1.055)
CapExp/Assets		1.426		1.682
		(1.465)		(1.726)
Leverage		-1.834***		-2.021***
		(0.384)		(0.459)
Tobin's Q		0.142***		0.130***
		(0.022)		(0.030)
Institutional Ownership		-0.229		-0.333
		(0.478)		(0.522)
Firm Age		0.000		0.000
		(0.000)		(0.000)
PPE/Assets		-0.806		-0.672
		(0.709)		(0.894)
Herfindahl Index		-0.561**		-0.345
		(0.274)		(0.328)
Constant	-1.851***	-2.340***	-4.158***	-3.690***
	(0.602)	(0.811)	(0.519)	(0.835)
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	1,832	1,644	1,832	1,644
R^2	0.377	0.408	0.329	0.347

Table 4: Investment Duration in Past Successful Projects and Startup Innovation

The dependent variable is the natural logarithm of the number of patents in a year in models (1) and (2), and is the natural logarithm of the number of citations per patent in a year in models (3) and (4). The observation unit in this analysis is IPO firm-year. The Huber-White-Sandwich robust standard errors (in parentheses) are clustered by IPO firm. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

	Ln(Patents)		Ln(Citations/Patent)	
	(1)	(2)	(3)	(4)
Ln(Duration in Success)	0.087	-0.074	0.045	-0.087
	(0.115)	(0.126)	(0.091)	(0.102)
Ln(Failure Tolerance)		0.416***		0.369***
		(0.115)		(0.100)
Ln(Sales)	0.100***	0.099***	0.033**	0.033**
	(0.021)	(0.021)	(0.015)	(0.015)
ROA	0.428***	0.457***	0.242*	0.265*
	(0.150)	(0.152)	(0.134)	(0.136)
R&D/Assets	1.348***	1.369***	1.089***	1.124***
	(0.306)	(0.310)	(0.266)	(0.269)
CapExp/Assets	0.570	0.650	0.274	0.330
	(0.678)	(0.693)	(0.683)	(0.691)
Leverage	-0.817***	-0.832***	-0.784***	-0.808***
	(0.189)	(0.194)	(0.144)	(0.146)
Tobin's Q	0.099***	0.103***	0.074***	0.077***
	(0.016)	(0.016)	(0.013)	(0.013)
Institutional Ownership	1.164***	1.100***	1.001***	0.948***
	(0.211)	(0.215)	(0.157)	(0.160)
Firm Age	0.047**	0.050**	0.004	0.007
	(0.020)	(0.020)	(0.011)	(0.011)
PPE/Assets	-0.310	-0.284	-0.342	-0.303
	(0.413)	(0.425)	(0.345)	(0.350)
Herfindahl Index	-0.032	-0.008	-0.058	-0.044
	(0.194)	(0.204)	(0.158)	(0.164)
Constant	-6.778***	-6.891***	-4.941***	-5.123***
	(1.072)	(0.606)	(0.831)	(0.662)
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	10,956	10,671	10,956	10,671
R^2	0.295	0.303	0.243	0.250

Table 5: Controlling for VC Project Selection Ability/Preference

This table reports the estimation of the extended empirical model (5). The observation unit in this analysis is IPO firm-year. The Huber-White-Sandwich robust standard errors (in parentheses) are clustered by IPO firm. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

Panel A: Number of Patents

Dependent Variable: Ln(Patents)	(1)	(2)	(3)
Ln(Failure Tolerance)	0.676***	0.655***	0.558**
	(0.235)	(0.210)	(0.229)
Investment Concentration	-0.793	-0.733	-0.686
	(1.047)	(0.882)	(0.923)
Past IPO Exit	1.759*	1.758*	1.459*
	(0.910)	(0.956)	(0.872)
% Investment in Early Ventures	-0.297	-0.278	-0.145
	(0.820)	(0.769)	(0.814)
Ln(Past No. of Firms Invested)	-0.026		
	(0.136)		
Ln(Past Fund Raised)		0.009	
		(0.071)	
Ln(VC Age)			0.251
			(0.174)
Controls, industry and year fixed effects	Yes	Yes	Yes
Lead VC fixed effects	Yes	Yes	Yes
Observations	11,239	11,239	11,232
R^2	0.448	0.448	0.448

Panel B: Patent Impact

Dependent Variable: Ln(Citations/Patent)	(1)	(2)	(3)
Ln(Failure Tolerance)	0.445**	0.423**	0.353**
	(0.176)	(0.174)	(0.177)
Investment Concentration	-0.634	-0.562	-0.502
	(0.719)	(0.667)	(0.650)
Past IPO Exit	1.176	1.188	1.004
	(0.778)	(0.777)	(0.782)
% Investment in Early Ventures	-0.603	-0.545	-0.479
	(0.577)	(0.582)	(0.579)
Ln(Past No. of Firms Invested)	-0.054		
	(0.112)		
Ln(Past Fund Raised)		-0.015	
		(0.061)	
Ln(VC Age)			0.148
			(0.132)
Controls, industry and year fixed effects	Yes	Yes	Yes
Lead VC fixed effects	Yes	Yes	Yes
Observations	11,239	11,239	11,232
R^2	0.350	0.350	0.350

Table 6: Recessions and the Failure Tolerance Effect

"Recession" is a dummy variable that equals one if an IPO firm received the first-round VC financing in a recessionary period, and equals zero otherwise. The recessionary periods are defined based on the NBER recession dates. Lead VC experience includes Investment Concentration, Past IPO Exit, and Ln(Past Fund Raised). The observation unit in this analysis is IPO firm-year. The Huber-White-Sandwich robust standard errors (in parentheses) are clustered by IPO firm. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

	Ln(Patents)		Ln(Citations/Patent)	
	Recession=1	Recession=0	Recession=1	Recession=0
	(1)	(2)	(3)	(4)
Ln(Failure Tolerance)	2.215***	0.597**	1.490**	0.402**
	(0.725)	(0.250)	(0.763)	(0.200)
IPO firm controls	Yes	Yes	Yes	Yes
Industry and year fixed effects	Yes	Yes	Yes	Yes
Lead VC experiences	Yes	Yes	Yes	Yes
Lead VC fixed effects	Yes	Yes	Yes	Yes
Observations	2,184	9,055	2,184	9,055
R^2	0.561	0.469	0.407	0.372

Table 7: Development Stage of Venture and the Failure Tolerance Effect

"Early Stage" is a dummy variable that equals one if an IPO firm was in the "Startup/Seed" stage or the "Early Stage" when it received the first-round VC investment as reported in the Venture Economics database, and equals zero otherwise. Lead VC experience includes Investment Concentration, Past IPO Exit, and Ln(Past Fund Raised). The observation unit in this analysis is IPO firm-year. The Huber-White-Sandwich robust standard errors (in parentheses) are clustered by IPO firm. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

	Ln(Patents)		Ln(Citations/Patent)	
	Early Stage=1	Early Stage=0	Early Stage=1	Early Stage=0
	(1)	(2)	(3)	(4)
Ln(Failure Tolerance)	0.763***	0.397	0.466**	0.055
	(0.174)	(0.442)	(0.189)	(0.433)
IPO firm controls	Yes	Yes	Yes	Yes
Industry and year fixed effects	Yes	Yes	Yes	Yes
Lead VC experiences	Yes	Yes	Yes	Yes
Lead VC fixed effects	Yes	Yes	Yes	Yes
Observations	7,117	4,122	7,117	4,122
R^2	0.478	0.568	0.380	0.420

Table 8: Cross-Industry Comparison of Failure Tolerance Effect

The "Drugs & Chemical" category includes industries that mainly produce patents on drugs, medical instrumentation, and chemicals. The "Computers & Electrical" category includes industries that mainly produce patents on computers, communications technologies, and electrical technologies. The "Software" category includes industries that mainly produce patents on software programming and internet applications. The "Low-Tech" category includes industries that produce other miscellaneous patents. Lead VC experience includes Investment Concentration, Past IPO Exit, and Ln(Past Fund Raised). The observation unit in this analysis is IPO firm-year. The Huber-White-Sandwich robust standard errors (in parentheses) are clustered by IPO firm. *** and ** indicate significance at the 1% and 5% levels, respectively.

Panel A: Number of Patents

Dependent Variable: Ln(Patents)	Drugs & Chemical (1)	Computers & Electrical(2)	Software (3)	Low-Tech (4)
Ln(Failure Tolerance)	0.771***	0.354***	0.170*	0.299*
	(0.209)	(0.096)	(0.095)	(0.181)
IPO firm controls	Yes	Yes	Yes	Yes
Lead VC fixed effects	Yes	Yes	Yes	Yes
Lead VC experience	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	2,997	3,421	2,721	2,100
R^2	0.297	0.368	0.217	0.610

Panel B: Patent Impact

Dependent Variable: Ln(Citations/Patent)	Drugs & Chemical (1)	Computers & Electrical (2)	Software (3)	Low-Tech (4)
Ln(Failure Tolerance)	0.601***	0.410***	0.209*	0.181
	(0.161)	(0.100)	(0.118)	(0.166)
IPO firm controls	Yes	Yes	Yes	Yes
Lead VC fixed effects	Yes	Yes	Yes	Yes
Lead VC experience	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	2,997	3,421	2,721	2,100
R^2	0.325	0.267	0.174	0.545

Table 9: Capital Constraints and VC Failure Tolerance

This table presents the dynamic pattern of VC's failure tolerance after a big fundraising event. "Failure Tolerance" in this table is the average duration of a VC's eventually failed projects in the past 5 years. "Fundraising Year" is defined as the calendar year in which the VC firm raises the largest amount of funding in our sample period. "1 (2, 3, 4) year(s) After Fundraising Year" equals one for event year 1 (2, 3, 4) after the fundraising year (year 0) and 0 otherwise. "Young (Old)" in models (2) and (3) mean the VC is younger (seven or older) than seven at the fundraising year. "Less (More) Exp." In models (4) and (5) mean the VC has invested in less than (at least) 21 ventures. The observation unit in this analysis is VC firm-year. The Huber-White-Sandwich robust standard errors (in parentheses) are clustered by VC firm. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

Dependent variable: Ln(Failure Tolerance)	Full Sample	VC Age		Past No. of Firms	
		Young	Old	Less Exp.	More Exp.
	(1)	(2)	(3)	(4)	(5)
1 Year After Fundraising Year	0.046**	0.062**	0.027	0.100***	0.004
	(0.019)	(0.026)	(0.027)	(0.026)	(0.021)
2 Years After Fundraising Year	0.100***	0.138***	0.042	0.211***	0.003
	(0.027)	(0.037)	(0.043)	(0.038)	(0.035)
3 Years After Fundraising Year	0.155***	0.214***	0.082*	0.298***	0.031
	(0.034)	(0.048)	(0.048)	(0.049)	(0.043)
4 Years After Fundraising Year	0.169***	0.236***	0.071	0.322***	0.050
	(0.038)	(0.056)	(0.054)	(0.058)	(0.047)
Industry Concentration	-0.715***	-0.612***	-0.932***	-0.398***	-0.718***
	(0.109)	(0.136)	(0.179)	(0.139)	(0.273)
% Investment in Early Ventures	0.141	0.082	0.760***	0.219**	0.295
	(0.096)	(0.112)	(0.203)	(0.108)	(0.206)
Constant	0.751***	1.326***	1.559***	1.321***	0.108
	(0.252)	(0.247)	(0.425)	(0.203)	(0.126)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	3,139	1,954	1,125	1,946	1,183
R^2	0.177	0.203	0.199	0.172	0.212

Table 10: Career Concerns and VC Failure Tolerance

This table presents the effect of a VC's career concerns on its failure tolerance. The dependent variable is the natural logarithm of VC failure tolerance (the 10-year rolling window measure). In Panel B, "Young (Old)" models (2) and (3) mean the VC is younger (seven or older) than seven. "Less (More) Exp." in models (4) and (5) mean the VC has invested in less than (at least) 21 ventures in the past 10 years. For the full sample, "Recently Successful" equals one if the VC's IPO exit rate is greater than 15% (the median value of *Past IPO Exit* for all VCs), and zero otherwise. For young and less experienced VCs, "Recently Successful" equals one if the VC's IPO exit rate is greater than 8% (the median value of *Past IPO Exit* for young VCs), and zero otherwise. For an old VC or a more experienced VC, "Recently Successful" equals one if the VC's IPO exit rate is greater than 18% (the median value of *Past IPO Exit* for old VCs), and zero otherwise. The observation unit in this analysis is VC firm-year. The Huber-White-Sandwich robust standard errors (in parentheses) are clustered by VC firm. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

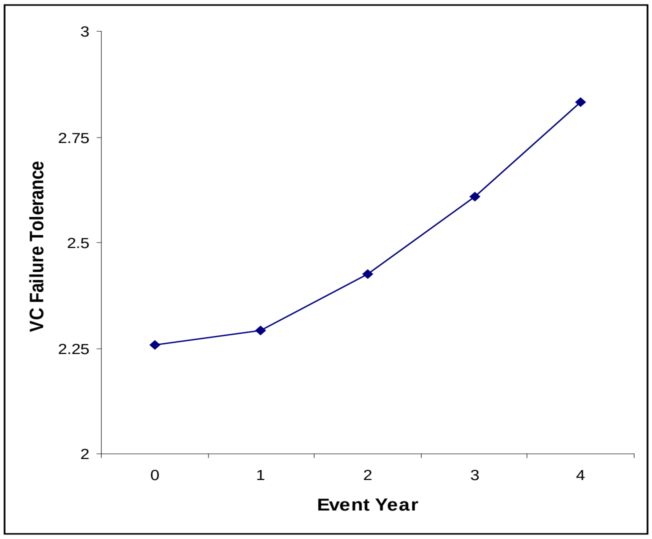
Panel A: VC Investment Experience and Failure Tolerance

Dependent variable: Ln(Failure Tolerance)	(1)	(2)	(3)	(4)
Ln(VC Age)	0.143***		0.061***	
	(0.012)		(0.021)	
Ln(Past No. of Firms Invested)		0.207***		0.069***
		(0.012)		(0.012)
Industry Concentration	-0.689***	-0.104	-0.163***	0.031
	(0.052)	(0.065)	(0.060)	(0.063)
% Investment in Early Ventures	0.258***	0.283***	0.061	0.069
	(0.049)	(0.047)	(0.047)	(0.045)
Constant	0.325**	0.177	0.261***	0.203**
	(0.151)	(0.145)	(0.089)	(0.094)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
VC firm fixed effects	No	No	Yes	Yes
Observations	14,786	14,917	14,786	14,917
R^2	0.217	0.255	0.885	0.883

Panel B: Impact of Recent Success on Failure Tolerance

Dependent variable: Ln(Failure Tolerance)	Full Sample	VC Age		Past No. of Firms	
		Young	Old	Less Exp.	More Exp.
	(1)	(2)	(3)	(4)	(5)
Recently Successful	0.106***	0.110***	0.010	0.094***	0.020
	(0.023)	(0.030)	(0.029)	(0.028)	(0.028)
Industry Concentration	-0.740***	-0.399***	-1.126***	-0.321***	-0.990***
	(0.052)	(0.061)	(0.082)	(0.060)	(0.135)
% Investment in Early Ventures	0.198***	0.240***	0.276***	0.246***	0.311***
	(0.047)	(0.050)	(0.092)	(0.049)	(0.110)
Constant	0.751***	1.326***	1.559***	1.321***	0.108
	(0.252)	(0.247)	(0.425)	(0.203)	(0.126)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	15,262	7,069	7,703	9,043	5,861
R^2	0.182	0.165	0.202	0.114	0.234

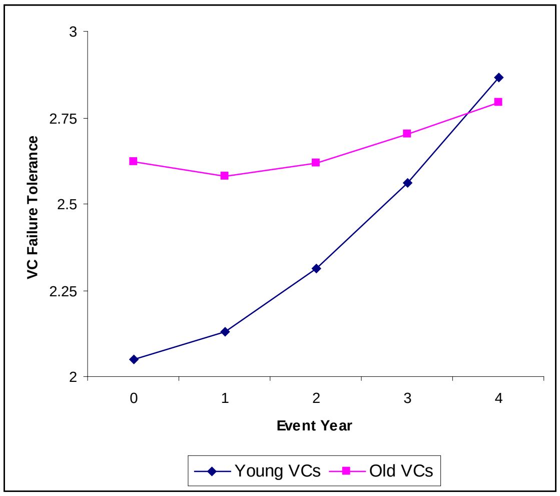
Figure 3



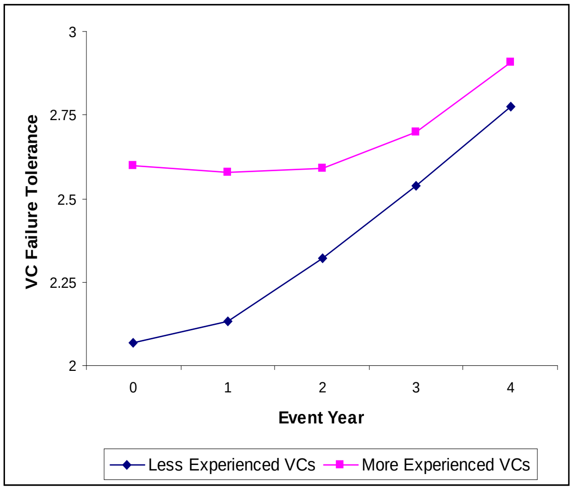
This figure presents the effect of fundraising on VC failure tolerance. Event year 0 is the calendar year in which the VC firm raises the largest amount of funds in our sample period.

Figure 4

Panel A

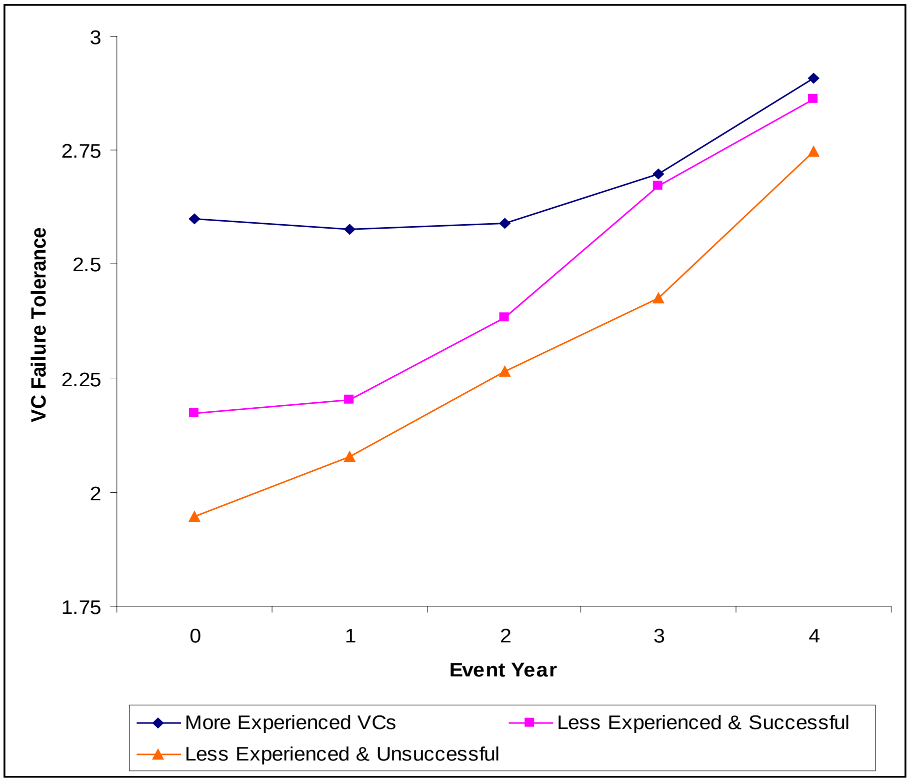


Panel B



These two figures present the effects of fundraising on VC failure tolerance based on VC age and past number of ventures invested. Year 0 is the year in which the VC firm raises the largest amount of funds in our sample period. “Young (Old) VCs” are VCs that are younger (seven or older) than seven at year 0. “Less (More) Experienced VCs” are VCs that have invested in less than (at least) 21 ventures in the past 10 years at year 0.

Figure 5



This figure presents the effect of fundraising on VC failure tolerance separately for more experienced VCs, less experienced but successful VCs, and less experienced and unsuccessful VCs. Event year 0 is the calendar year in which the VC firm raises the largest amount of funds in our sample period. "Less (More) Experienced VCs" are VCs that have invested in less than (at least) 21 ventures in the past 10 years at year 0. "Less Experienced & Successful" are less experienced VCs that have had an IPO exit rate of at least 8% in the past 10 years. "Less Experienced & Unsuccessful" are less experienced VCs that have had an IPO exit rate lower than 8% in the past 10 years.