TOLERANCE FOR FAILURE AND CORPORATE INNOVATION

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This version: July, 2010

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

JEL classification: M14, O31, G24, G34

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* We are grateful for comments from Utpal Bhattacharya, Henrik Cronqvist, Douglas Cumming, Nishant Dass, David Denis, William Kerr, Gustavo Manso, Robert Marquez, Raghuram Rajan, Amit Seru, Merih Sevilir, Ann Sherman, PK Toh, Andrew Winton, and Ayako Yasuda. We also thank seminar participants at University of Minnesota, the Fifth Annual Early-Career Women in Finance Conference, the State of Indiana Conference, the Sixth Annual Corporate Finance Conference at Washington University in St. Louis, the NBER Entrepreneurship 2009 Winter Group Meeting, the SunTrust Bank Spring Beach Conference at Florida State University, the 2010 Napa Conference on Financial Markets Research, the 2010 Financial Intermediation Research Society Conference, the 2nd ESSEC Private Equity Conference, the Entrepreneurial Finance and Innovation Conference, the Conference on People & Money at DePaul University, and the 2010 China International Conference in Finance.

TOLERANCE FOR FAILURE AND CORPORATE INNOVATION

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's 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, i.e., ventures born in recessions, ventures at early development stages, and ventures in industries in which innovation is difficult to achieve.

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 (2010) 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 the principal investors and important decision makers in the startup firms they finance. They have the final decision power on whether to continue investment or to terminate a project. If VC investors are not tolerant of 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] Ederer and Manso (2010) conduct a controlled laboratory experiment and provide evidence supporting the implications in Manso (2010).

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.

Although 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 of the results 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. We thus do a rich set of analysis to address this identification problem.

We first extend the basic model of VC project termination to allow for heterogeneity in VC investors' project selection abilities that directly impact the matching between VC investors and projects. The extended model provides a clear structure for the causes and solutions to the endogeneity problem. Following the model's guidance, we then show that the effect of VC failure tolerance on startup firm innovation cannot be explained away (in fact, the effect is even stronger) by including the lead VC firm fixed effects, which absorb the time-invariant differences in project selection abilities across lead VC investors. Further, besides VC fixed effects we control for the possible time-varying component of the VC project selection abilities by including the VCs' past investment experiences and industry expertise. Again, we find that the failure tolerance effect is not only present but even stronger. Finally, we decompose our failure tolerance measure and remove the VC project selection component from the measure. We find that the variation of the "purer" VC failure tolerance measure continues to powerfully explain the variation in the IPO firm's innovation productivity.

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.

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, market timing abilities, 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, Gompers, Kovner, and Lerner 2009, and Puri and Zarutskie 2009). In particular, Kortum and Lerner (2000) find that increases in VC activity in an industry lead to significantly more 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 concludes.

2. MEASURING FAILURE TOLERANCE

2.1 VC Firm's Failure Tolerance: A Conceptual Framework

Failure in this study means unsatisfactory progress in the innovation process. We wish to infer a VC firm's tolerance for failure by examining its tendency to continue investing in a project conditional on the project not meeting stage targets. It is well known that VC investments are highly risky due to the nature of the business. This is why the staging of capital infusions is an essential feature of VC investments (Gompers 1995). 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

[2] Other papers have examined the effect of ownership structure and financing on corporate innovation (e.g., Atannassov, Nanda, and Seru 2007, Seru 2008, Aghion, Van Reenen, and Zingales 2009, Belenzon and Berkovitz 2010, and Lerner, Sorensen, and Stromberg 2010).

terminating funding immediately should to some extent reflect a VC's attitude towards failures in investments. Put differently, a VC's failure tolerance resides in its power of termination.

A challenge for us is how to empirically capture "conditional on the project not meeting stage targets." Ideally, we would like to observe the ex-post stage performance of a venture relative to the ex-ante stage targets specified in the contract between the VC and the entrepreneur, and the VC's decision after reviewing the venture's performance at each investment round (i.e., continued investment or termination of funding). Unfortunately, the available VC investment data only provide information about the VC's decision at each investment round, but do not provide the conditioning information (e.g., whether the project meets the stage targets). [3] This data limitation implies that we have to measure a VC's failure tolerance in an indirect way. Thus we present a simple illustrative model to examine how VC investors exercise their option to terminate a project upon receiving negative information, and use the model implication to motivate our empirical measure of 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. Without loss of generality, we set the threshold to be zero,

[3] An alternative way to capture "conditional on the project not meeting stage targets" is to examine a VC's tendency to invest in a down round, i.e., an investment round in which the post-round valuation is lower than the prior-round valuation. However, only 16.9% of VC financing rounds reported in our VC database (the Thomson Venture Economics) has information about the post-round valuation, which largely reduces the sample size and may expose our study to serious sample selection problems.

consistent with the positive NPV investment rule. Thus the VC will terminate the project after receiving the *n*-th signal, where *n* is the smallest integer that satisfies the following condition:

$$\theta + E(u \mid \delta_1, \delta_2, ..., \delta_n) \le 0 \qquad (1)$$

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

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

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.

How does failure tolerance affect the VC's project termination decision? Note that failure tolerance in this study is meant to capture the VC's tendency to continue investing in a project conditional on the project underperforming (i.e., conditional on a negative performance signal). We can view failure tolerance as the VC's preference that affects how it reacts to initial negative performance signals. Given a negative signal, a failure-intolerant VC tends to adjust the project NPV estimate downward more than a failure-tolerant VC does. As a result, the failure-intolerant VC tends to terminate a project more quickly upon receiving negative signals.

There are different ways to model such preference. We think that a simple way is as follows. Let h_ε^i denote VC-*i*'s perceived precision of the signal noise. We assume that

$$h_\varepsilon^i = \phi^i h_u\ . \qquad (3)$$

Making h_ε^i proportional to h_u means that projects with higher uncertainty also tend to have noisier signals. More importantly, $\phi^i > 0$ introduces heterogeneity among VCs. VCs with a high ϕ^i are failure-intolerant. They perceive the initial negative signals as very informative and adjust their estimates of u accordingly. VCs with a low ϕ^i are failure-tolerant. They view the initial negative signals as less informative and thus do not adjust their posterior NPV estimate downward much. Therefore, a lower ϕ^i means a higher level of failure tolerance.

Note that our intention is not to argue which type of VCs is more correct or more rational because we assume that nobody observes the true signal noise precision h_ε. This is a reasonable assumption given the exceptionally high uncertainty in the initial stages of an innovation process, creating discretion in interpretations and room for judgment. All VC investors behave rationally according to their beliefs and preferences. Also, our model is not about different VCs being differentially informed. It is about different VC beliefs and preferences leading to different reactions to the same information.

Plugging (3) into equations (1) and (2), VC-*i*'s investment duration in an eventually failed project is the smallest integer *n* so that $n^i \geq (\frac{1}{\phi^i})\frac{\theta}{(-\bar{\delta})-\theta}$. Taking the logarithm on both sides of the inequality and letting $c \equiv \log(\frac{\theta}{(-\bar{\delta})-\theta})$, we have

$$\log(n^i) \approx \log(\frac{1}{\phi^i}) + c. \qquad (4)$$

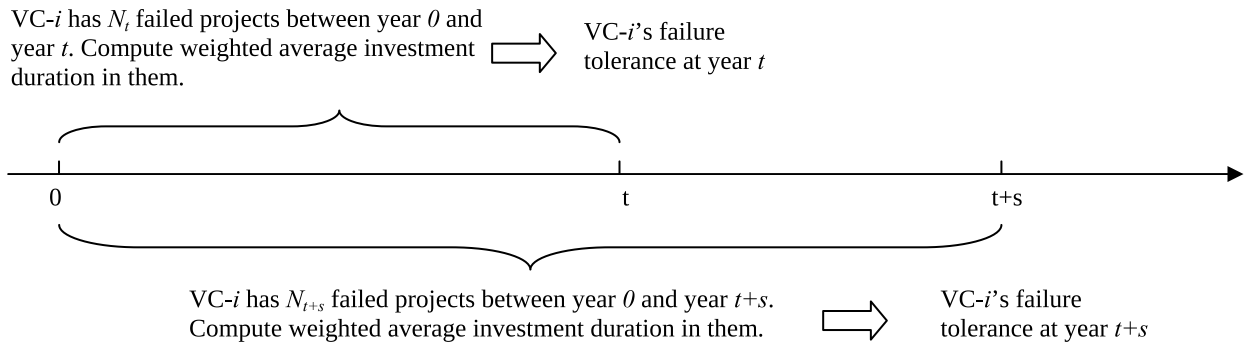
Equation (4) is the key equation that provides the conceptual foundation for our empirical measure. It shows that the VC's investment duration in an eventually failed project can serve as a measure of the VC's failure tolerance. The lower the ϕ^i is, the more failure tolerant the VC is, and the longer the investment duration $\log(n^i)$ is.

2.2 VC Firm's Failure Tolerance: The Empirical Measure

Following the implication of equation (4), 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 up to year *t* (see Figure 1 for an illustration). Failed projects are those that are eventually written off by their investing VC investors. 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 up to 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 up to year *t*+*s*. Since the number of a VC's failed projects accumulates over time, the failure tolerance measure is time-varying, allowing the VC investors' attitude towards failure to slowly change over time.[4]

Figure 1: VC Firm's Failure Tolerance



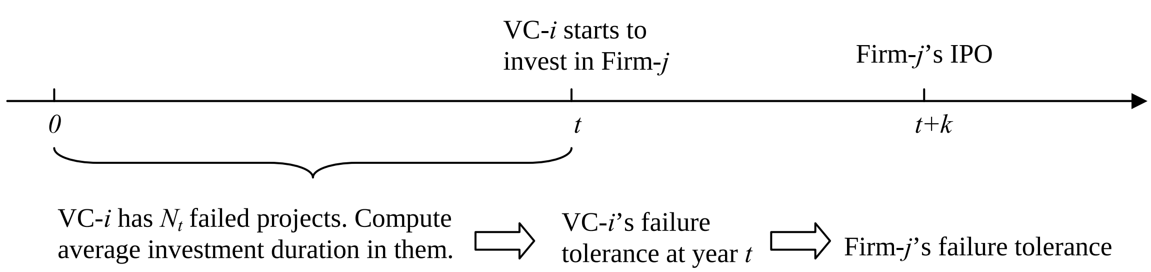
We obtain data on round-by-round VC investments from the Thomson Venture Economics database for entrepreneurial firms that received VC financing between 1980 and 2006.[5] Appendix A point A discusses the details of the data cleaning. To construct the VC failure tolerance measure, we focus on VC firms' failed investments, i.e., entrepreneurial firms that were 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 Economics, we classify a firm as a written-off firm if it did not receive any financing within a ten-year span after its very last financing round.

[4] 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.
[5] 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.

There are 18,546 eventually failed ventures receiving 67,367 investment rounds from 4,910 VC firms in our sample. For each failed venture a VC firm 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 0.63.

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 sum, 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.

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.[6] 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.

[6] 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

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., Lee and Wahal 2004, Nahata 2008), 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 two years and seven months and it can be as long as six years and ten months. The average *VC Syndicate Failure Tolerance* is about one year and ten months. 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, which is also consistent with equation (4).

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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.

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:

$$Ln(Innovation_{j,t}) = \alpha + \beta \times Ln(FailureTolerance^{i}_{j,0}) + \gamma Z_{j,t} + Ind_j + Year_t + v_{j,t} \quad (5)$$

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 two-digit SIC industry fixed effects and fiscal year fixed effects, respectively.

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 also use both cross-sectional regressions as well as the Fama-Macbeth regressions.

3.1 Proxies for Innovation

The innovation variables are constructed from the latest version of the 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 (5), 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.[7]

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 innovative projects (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.

[7] 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.

We extract financial information for the IPO firms from Standard & Poor's COMPUSTAT files, stock prices and shares outstanding data from CRSP, and institutional investors' ownership from the Thomson Financial 13f institutional holdings database. In the end, there are 1,848 VC-backed IPO firms in our sample with non-missing VC investor characteristics, financial and ownership information.

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 total book assets of $485.5 million, 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* is 0.567. This means that a one percent increase in *Failure Tolerance* on average leads to more than a half 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 1.8 years before terminating a project. If this VC firm is willing to invest for 3.4 years before giving up a project (the 75th percentile of the failure tolerance distribution), then holding everything else equal the IPO firms backed by this VC firm tend to have 50.4% ($=\frac{3.4-1.8}{1.8}*0.567$) 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 0.258. Not surprisingly, the marginal impact of VC syndicate's failure tolerance on the IPO firm's innovation is much smaller than that of the lead VC's failure tolerance. This implies that the lead VC investor's attitudes towards failure matters a lot 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 0.5 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). In un-tabulated regressions, we also exclude self-citations when computing citations per patent. Our results are robust to such modification.[8]

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), older, and have more growth potential (higher *Q*) and lower exposure to financial distress (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. Larger investment in fixed assets (higher capital expenditures) is also associated with higher innovation productivity. Further, higher institutional ownership is associated with more innovation, which is consistent with the findings in Aghion, Van Reenen, and Zingales (2009). Finally, asset tangibility (measured by the 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 (2010) 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

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[8] For example, the coefficient estimate of *Ln(Failure Tolerance)* is 0.550 (p-value<0.001) in model (3) of Table 2 when the natural logarithm of the non-self citations per patent is the dependent variable.

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 the alternative measure of failure tolerance, *Failure Tolerance 2*, which is based on the average number of financing rounds the lead VC investor made in its past failed projects. For example, the coefficient estimate for *Ln(Failure Tolerance 2)* in model (1) of Table 2 is 0.217 (p-value = 0.05), and is 0.220 (p-value = 0.01) in model (3).

Focusing on the subsample of firms that has 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 0.372 (p-value = 0.05), and is 0.373 (p-value = 0.01) 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 0.567 (p-value < 0.001) in model (1) of Table 2, and is 0.504 (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 0.575 (p-value < 0.001) in model (1) of Table 2, and is 0.547 (p-value < 0.001) in model (3).

In Table 2 we control for industry fixed effects at the two-digit SIC level. Alternatively, we control for industry fixed effects using three-digit SIC and four-digit SIC, and the baseline results hold. We also use the 10-industry, 18-industry, and 354-industry specifications in the Venture Economics database for the industry fixed effects, 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 = 0.589, p-value = 0.03), but the coefficient estimate of the squared term is negative and statistically insignificant (coefficient = -0.067, p-value = 0.19). We find similar results for patent citations. The evidence suggests that the effect of failure tolerance on innovation productivity is positive and monotonic in our sample.

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 were filed by each IPO firm within the first five years after IPO and the average number of citations each of these patents received. We impose the arbitrary five-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 39% 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.[9]

5. EMPIRICAL IDENTIFICATION

Although our baseline results are consistent with the hypothesis that VC investors' failure tolerance leads to higher ex-post innovation productivity in VC-backed startup firms, an alternative interpretation of the results could be that failure-tolerant VCs as specified in our study

[9] 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.

are in equilibrium matched with firms that have high ex-ante innovation potentials, and high ex-ante potentials lead to high ex-post outcomes.

In this section we address this alternative explanation as follows. First, we extend the simple model in Section 2.1 to allow for the above endogeneity. Then we rely on the model to understand the nature of the endogeneity problem and to find the appropriate solution. Second, we look for further evidence of identification in the cross section. We show that the marginal effect of VC failure tolerance on startup innovation is much stronger in ventures in which the failure risk is higher and thus VC's tolerance for failure is more needed and valued.

5.1 What could be the Omitted Variables?

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 suppose that different VCs have different project selection preferences or abilities.[10] 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. This is the only departure from the basic model in Section 2.1. The rest of the assumptions are the same as in the basic model.

VC-*i* will stop investing in the project when $\theta^i + E(u \mid \delta_1, \delta_2, ..., \delta_n) \le 0$. This implies that VC-*i*'s investment duration in an eventually failed project is the smallest integer n so that $n^i \ge (\frac{1}{\phi^i})\frac{\theta^i}{(-\bar{\delta}) - \theta^i}$. Taking the logarithm on both sides of the inequality, we have

$$\log(n^i) \approx \log(\frac{1}{\phi^i}) + \log(\frac{\theta^i}{(-\bar{\delta}) - \theta^i})\,. \quad (6)$$

Equation (6) provides guidance for our empirical identification. If different VCs have different project selection abilities, a VC firm's investment duration in an eventually failed

[10] 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.

project is positively related to not only the VC's tolerance for failure ($1/\phi^i$) but also its project selection ability (θ^i). Holding the VC's failure tolerance constant, the better the projects are on average (i.e., a higher θ^i), the longer the VC is willing to invest in projects that underperform and eventually fail. The average signal $\bar{\delta}$ is a function of the project's idiosyncratic quality u. Thus we can write our main explanatory variable in the baseline regression (5) as

$$Ln(FailureTolerance^i) = f(\phi^i, \theta^i, u_{past}),$$

where u_{past} represents the idiosyncratic qualities of VC-*i*'s past failed projects.

The dependent variable in the baseline regression is the ex-post innovation productivity of a future successful project-*j* undertaken by VC-*i*. Our hypothesis is that project-*j*'s ex-post innovation outcome depends on VC-*i*'s failure tolerance ($1/\phi^i$). But the ex-post innovation outcome certainly depends on the ex-ante innovation potential of the project as well, which is related to the quality of project-*j*, $\eta_j = \theta^i + u_j$. We can interpret u_j as the idiosyncratic characteristics of the future IPO firm-*j*. Then we can write our dependent variable as

$$Ln(Innovation_j) = g(\phi^i, \theta^i, u_j).$$

Now we can clearly see that θ^i can introduce an omitted variable problem in our baseline regression. 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.[11]

However, our model implies that neither u_{past} nor u_j introduces an omitted variable problem in the baseline regression. This is because projects undertaken by the same VC at different points of time 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. Thus although u_{past} affects our independent variable, it does not affect the dependent variable. Similarly, although u_j affects our

[11] 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 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.

dependent variable, it does not affect our independent variable and thus won't bias our estimate of β in the baseline regression. 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.

5.2 Controlling for VC Firm Project Selection Ability

5.2.1 Extended Empirical Model

How can we effectively control for the omitted variable problem related to θ^i ? If information in VC-*i*'s past failed projects can help predict the innovativeness of its future successful projects through θ^i , then θ^i should exhibit predictability over time.

The simplest case is that θ^i is constant over time. That is, the VC firm's project selection ability or investment preference does not change over time. In this case, including VC firm fixed effects can effectively control for the omitted variable problem. 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 have a time-varying component. That is, $\theta_t^i = \theta^i + \varphi_t^i$. If the time-varying component φ_t^i is independent over time, then including VC firm fixed effects is again sufficient for addressing the omitted variable problem. This is because the φ related to past failed projects cannot predict the φ related to future projects.

More likely, the time-varying component of θ_t^i may exhibit a predictable time trend. A reasonable conjecture is that the VC firm becomes better at project selection as it accumulates investment experiences over time. Sorensen (2007) shows that more experienced VCs invest in better projects. Thus we assume that $\varphi_t^i = \varphi \times EXP_t^i$, 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 are omitted variables in the baseline regression. We need to explicitly control for both.

In sum, to control for the VC's project selection ability, we extend our baseline regression to include both the lead VC firm fixed effects and the lead VC firm time-varying investment experience and expertise and estimate the following model:

$$Ln(Innovation_{j,t}) = \alpha + \beta Ln(FailureTolerance_{j,0}^i) + \varphi EXP_{j,0}^i + \theta^i + controls + v_{j,t} \quad (7)$$

Both VC-i's failure tolerance and its experience 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 four VC general investment experience measures: a) the total dollar amount the VC firm has invested since 1980 (*Past Amount Invested*); b) the total number of firms the VC firm has invested in since 1980 (*Past Firms Invested*); c) the total dollar amount the VC firm has raised since 1965 (*Past Fund Raised*); and d) 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, may also capture the degree of capital constraint the VC firm faces.

A VC's project selection ability may be best reflected in its past successes. For each VC firm and each year, we compute *Past Successful Exit* as the proportion of entrepreneurial firms financed by the VC firm that have exited successfully through either going public or acquisition since 1980. The VC literature suggests that going public is a more desirable outcome than acquisitions 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 2008). Therefore, we also calculate *Past IPO Exit* as the fraction of entrepreneurial firms financed by the VC firm that has gone public since 1980.

Another important dimension of a VC firm's experience is its 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 increases as the VC's portfolio becomes more concentrated in a few industries.

Table 1 Panel A shows that the average lead VC firm in a given year is about 14 years old and has invested 1.4 billion dollars in 97 entrepreneurial firms. Among all ventures the average lead VC firm has financed, 69% had a successful exit but only 24% went public. The average lead VC's portfolio firms are concentrated in a few industries with the investment concentration index of 0.10.

Table 4 reports the results from the extended empirical model (7). We start by adding the lead VC firm fixed effects to the baseline regression in Panel A. Interestingly, the marginal effect of VC failure tolerance on IPO firm innovation becomes even stronger. The estimated elasticity of patents to *Failure Tolerance* is 0.748, higher than 0.567 in the baseline regression in Table 2. The estimated elasticity of patent citations to *Failure Tolerance* is 0.682, also higher than 0.503 in the baseline regression. These results imply that the effect of VC failure tolerance on IPO firm innovation is not driven by average unobservable heterogeneity across VC firms. The within-VC firm variation in failure tolerance actually has a stronger predictive power for IPO firm innovation than does the between-VC firm variation in failure tolerance. As the lead VC investor becomes more failure-tolerant, the IPO firms financed by this VC investor exhibits higher innovation productivity.

In Table 4 Panel B we include both the lead VC firm fixed effects and the time-varying VC investment experience to control for both the time-invariant and time-varying components of VC project selection ability. Since the four VC general investment experience variables are highly correlated with each other, we include them one by one in the regressions. We find that VC failure tolerance still has a positive and significant effect on startup firms' innovation productivity. The average estimated elasticity of patents to *Failure Tolerance* is 0.757, and the average estimated elasticity of patent citations to *Failure Tolerance* is 0.765. Further, after controlling for VC failure tolerance, the other VC firm characteristics largely do not affect the innovation productivity of the IPO firms.

5.2.2 Orthogonalized VC Failure Tolerance Measure

As a further identification test, we try to remove other possible determinants of a VC's investment duration in past failed projects in order to examine the effect of a "purer" measure of VC failure tolerance. This analysis involves two stages. In the first stage, we regress a VC's average investment duration in eventually failed projects (our VC failure tolerance measure) on possible determinants other than VC failure tolerance. Then in the second stage, we use the residual term from the first-stage regression as a new proxy for VC failure tolerance and re-estimate the failure tolerance effect.

The first-stage regression is as follows.

$$Ln(FailureTolerance_t^i) = \gamma_0 + \gamma_1 EXP_t^i + \theta^i + Ind_j + Year_t + w_t^i \qquad (8)$$

We include VC firm fixed effects (θ^i) and time-varying VC investment experiences (EXP_t^i) to control for the effect of VC project selection ability. The investment cycle may be different in different industries, driving the variation in the average investment duration across industries. Some lead VC firms invest in multiple industries. Thus besides VC fixed effects, we further control for the failed entrepreneurial firms' industry fixed effects based on the 18-industry classification in Venture Economics (Ind_j).[12] Lastly, we include year fixed effects ($Year_t$) to absorb any possible determinant that varies only by year. Also note that in the first-stage analysis, we use the entire investment history of the 638 lead VC firms that appear in our IPO sample, which contains additional information relative to that reported in Table 1 for the IPO sample.

The first-stage results are reported in Table 5 Panel A. The observation unit in this analysis is VC firm-year. In all four models, the coefficient estimates of VC investment experience proxies are positive and significant. Since we control for VC firm fixed effects, these results imply that as a VC firm accumulates investment experience over time, its project selection ability improves, making it willing to invest longer in projects that eventually failed. This is consistent with the implication of equation (6). The effect of a VC firm's investment concentration is weaker and is significantly positive in two out of four models. The effect of a VC's *Past IPO Exit* rate is statistically insignificant in all four models. We find similar results when replacing the VC's past IPO exit rate with its past successful exit rate. These results imply that after controlling for VC's investment experiences, industry specialization and past successful experiences do not impact the VC's project termination decisions.

The positive relationship between VC experience and the failure tolerance measure also mitigates a potential concern that long investment duration in an eventually failed project reflects a VC firm's inability to efficiently terminate unpromising projects. If experienced VC investors know when to pull the plug in unpromising deals and less sophisticated ones wait for too long, then we should have seen a negative relationship between the failure tolerance measure and VC experience proxies. Further, if our failure tolerance measure proxies for excessive project continuation, then it should not be systematically associated with good outcomes in IPO firms.

In the second stage, we use the residual term from the first-stage regression as a new proxy for VC failure tolerance, and call it *Orthogonalized Failure Tolerance*. We then re-

[12] 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.

estimate our baseline regressions in equation (5) using this new independent variable. The results are reported in Table 5 Panel B. The average estimated elasticity of patents to the orthogonalized failure tolerance measure in the four models is 0.473, which is comparable to the estimated elasticity in the baseline regression (0.567). The average estimated elasticity of patent citations to the orthogonalized failure tolerance measure in the four models is 0.508, which is similar to that in the baseline regression (0.503). The regression R-squared is also similar to those in the baseline regressions.

Note that the first-stage models in Panel A on average explain about 78% of the variation in *Ln(FailureTolerance)*. Panel B shows that the remaining 22% of the variation in the VC failure tolerance measure captured by *Orthogonalized Failure Tolerance* has almost the same explanatory power for ex-post startup innovation as the raw failure tolerance measure. This implies that although VC project selection abilities along with other determinants well explain VC investment duration in past failed projects, they do not contribute to the positive relationship between such investment duration and ex-post innovation productivity of startup firms.

In sum, results in Tables 4 and 5 suggest that VC project selection abilities are unlikely to drive the positive VC failure tolerance effect documented in our baseline regressions. Of course, a possibility that we cannot completely rule out in the above analysis is that the time-varying component of the VC project selection ability is poorly measured by the VC experience proxies we use. Thus next we explore cross-sectional heterogeneity in the VC failure tolerance effect for further identification.

5.3 Identification in the Cross Section

In this section, we rely on the cross-sectional variations in startups' failure risk to identify the failure tolerance effect. 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 and VC's failure tolerance can help a venture realize its innovation potentials, then we expect the marginal impact 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, 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. 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 realized 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 will slice the sample in three different dimensions to capture the cross-sectional differences in startups' failure risk: ventures' "birth" cohorts, development stages, and industries.

5.3.1 Recessions 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 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 (7) 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 1.951, almost triples the impact for firms not born in recessions (0.683). The results are similar for patent impact (1.889 vs. 0.652). 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 (as proxied by being born in a recession) does not necessarily imply that the marginal impact of ex-ante quality on ex-post outcome should be higher for this group of firms.

5.3.2 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.

Then we estimate the extended empirical model (7) 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 1.058 and significant at the 1% confidence level, while it is 0.513 for late-stage ventures and is only marginally significant at the 10% level. The results are similar for patent impact (1.035 vs. 0.454). 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.

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 5.3.1, 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.

5.3.2 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).[13] If a firm has no patent, then we classify it into one of the above

[13] 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

four categories based on the type of patents that is most frequently produced by the firm's 3-digit SIC industry. For example, if a firm is in the industry with 3-digit SIC 283 and has no patent in the sample period, then it is classified under category (1) because 77% of the patents generated by the firm's industry are related to drugs and chemicals.

Common sense suggests that among the above four categories patents of new drugs are 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 (7) for each industry category separately. Table 8 shows that there is significant difference in the marginal impact of VC failure tolerance on startup innovation across industries. The effects of VC failure tolerance on the number of patents and the patent impact are positive and significant in the drugs industry, the computers/electrical industry, and the software industry, but are insignificant in the low-tech industry.

Also 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 1.695 in the drugs industry, more than doubles the effect in the software industry (0.714). The differences in the marginal impact of failure tolerance between the drugs industry and the software and low-tech 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 drugs industry, and is 3.21 for firms in other industries. Also, we have controlled for the VC firm

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and miscellaneous together because we do not have many observations of these patents and label this category as miscellaneous patents.

fixed effects, which removes the average differences in patenting propensity across VC firms and should subsume any average differences across industries.

In sum, the cross-sectional analysis in Section 5.3 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. CONCLUSION

The economic theories imply that tolerance for failure is crucial for a firm's innovation productivity. 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. Other things equal, the longer the VC investor on average waits before terminating funding in an underperforming project, the more tolerant it is for early failures in its investments. We then examine whether such failure tolerance spurs innovation in a sample of VC-backed IPO firms between 1985 and 2006.

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.

Our study also 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. Is the profit-maximizing level of failure tolerance for a VC firm consistent with the socially optimal level of failure tolerance? Future research that explores the source of VC failure tolerance, its evolution over time, and its impact on the VC's portfolio choice and payoff can potentially generate interesting insights on these questions.

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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 were 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* invested in its projects that were initiated in or after year 1980 and eventually failed in or before year *t*
Failure Tolerance 2$_{it}$	The average number of financing rounds VC firm *i* invested in its projects that were initiated in or after year 1980 and eventually failed in or before year *t*
Past Amount Invested$_{it}$	The total dollar amount invested by VC firm *i* since 1980 up to year *t*
Past Firms Invested$_{it}$	The total number of firms VC firm *i* has invested in since 1980 up to year *t*
Past Fund Raised$_{it}$	The total dollar amount raised by VC firm *i* since 1965 up to year *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 in 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 in 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 went public between year 1980 and year *t*
Past Successful Exit$_{it}$	The proportion of entrepreneurial firms financed by VC firm *i* that either went public or were acquired between year 1980 and year *t*
Early Stage$_{i}$	An indicator variable that equals one if a venture was in the “startup/seed” and “early stage” and zero if in “expansion”, “later stage”, “buyout/acquisition”, or “other” stages when it received the 1st round VC financing
Innovation Variables (data source: NBER Patent Data)	
Patents$_{it}$	Number of patents firm *i* applied for in year *t*. Only patents that were 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* applied 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	1.75	2.58	2.62	3.43	1.10	1,860
VC Syndicate Failure Tolerance	1.32	1.76	1.80	2.26	0.69	1,848
Failure Tolerance 2	2	2.95	3.06	3.96	1.43	1,871
VC Syndicate Failure Tolerance 2	2.18	2.82	2.90	3.53	1.04	1,871
Past Amount invested (mil)	135.48	543.79	1392.62	1531.07	2672.97	1,860
Past Firms invested	22	59	97.19	125	120.14	1,860
Past Fund Raised (mil.)	26.60	146.90	412.39	412.60	1008.03	1,860
VC Age	6	12	14.25	21	9.94	1,860
Investment Concentration	0.01	0.02	0.10	0.07	0.20	1,860
Past IPO Exit (%)	16.67	21.90	24.22	28.57	14.63	1,860
Past Successful Exit (%)	62.18	69.86	68.61	76.53	14.84	1,860
Early Stage	0	1	0.63	1	0.48	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)	0.567***		0.503***	
	(0.114)		(0.093)	
Ln(VC Syndicate Failure		0.258**		0.201**
Tolerance)		(0.113)		(0.093)
Ln(Sales)	0.094***	0.097***	0.028**	0.030**
	(0.019)	(0.019)	(0.013)	(0.014)
ROA	0.686***	0.677***	0.391***	0.388***
	(0.138)	(0.141)	(0.122)	(0.125)
R&D/Assets	1.445***	1.520***	0.994***	1.066***
	(0.284)	(0.286)	(0.247)	(0.248)
CapExp/Assets	1.953***	2.017***	1.150**	1.259**
	(0.573)	(0.586)	(0.572)	(0.584)
Leverage	-0.776***	-0.813***	-0.725***	-0.755***
	(0.160)	(0.162)	(0.130)	(0.133)
Tobin's Q	0.093***	0.093***	0.071***	0.071***
	(0.015)	(0.015)	(0.012)	(0.012)
Institutional Ownership	0.990***	1.006***	0.794***	0.812***
	(0.186)	(0.188)	(0.143)	(0.145)
Firm Age	0.060***	0.058***	0.019*	0.016
	(0.018)	(0.018)	(0.010)	(0.010)
PPE/Assets	0.093	0.124	-0.066	-0.078
	(0.344)	(0.361)	(0.305)	(0.317)
Herfindahl Index	-0.282	-0.252	-0.126	-0.095
	(0.177)	(0.181)	(0.155)	(0.158)
Constant	-3.181**	0.149	-2.874**	-3.139**
	(1.366)	(0.607)	(1.178)	(1.386)
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	12,102	11,994	12,102	11,994
R^2	0.323	0.315	0.260	0.253

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 were 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 were 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)	1.160***	1.087***	1.106***	1.022***
	(0.156)	(0.151)	(0.172)	(0.166)
Ln(Sales)		0.043*		0.022
		(0.024)		(0.026)
ROA		0.588		0.054
		(0.398)		(0.464)
R&D/Assets		2.316***		1.774*
		(0.819)		(0.993)
CapExp/Assets		1.448		1.909
		(1.424)		(1.573)
Leverage		-1.805***		-1.964***
		(0.377)		(0.433)
Tobin's Q		0.142***		0.121***
		(0.021)		(0.027)
Institutional Ownership		-0.307		-0.290
		(0.471)		(0.499)
PPE/Assets		-0.746		-0.668
		(0.688)		(0.808)
Herfindahl Index		-0.628**		-0.359
		(0.275)		(0.302)
Constant	-2.313***	-2.611***	-4.186***	-3.947***
	(0.645)	(0.806)	(0.499)	(0.768)
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	0.389	0.418	0.329	0.349

Table 4: Controlling for VC Project Selection Ability

This table reports the estimation of the extended empirical model (7). 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: Lead VC Firm Fixed Effects

	Ln(Patents) (1)	Ln(Citations/Patent) (2)
Ln(Failure Tolerance)	0.748***	0.682***
	(0.161)	(0.133)
Ln(Sales)	0.064***	0.016
	(0.018)	(0.015)
ROA	0.813***	0.467***
	(0.138)	(0.135)
R&D/Assets	1.229***	0.826***
	(0.267)	(0.261)
CapExp/Assets	0.879*	0.320
	(0.528)	(0.582)
Leverage	-0.587***	-0.534***
	(0.147)	(0.130)
Tobin's Q	0.070***	0.058***
	(0.012)	(0.013)
Institutional Ownership	0.903***	0.670***
	(0.165)	(0.151)
Firm Age	0.069***	0.020
	(0.019)	(0.013)
PPE/Assets	0.409	-0.031
	(0.368)	(0.345)
Herfindahl Index	-0.185	-0.037
	(0.158)	(0.137)
Constant	-2.449***	-2.575**
	(0.937)	(1.170)
Lead VC fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	12,102	12,102
R^2	0.456	0.351

Panel B: Both Lead VC Experience and Lead VC Fixed-Effects

Dependent Variable: Ln(Patents)	(1)	(2)	(3)	(4)
Ln(Failure Tolerance)	0.730***	0.741***	0.809***	0.747***
	(0.197)	(0.202)	(0.174)	(0.191)
Investment Concentration	-0.150	-0.170	-0.322	-0.167
	(0.353)	(0.364)	(0.315)	(0.324)
Past IPO Exit	-0.074	-0.076	-0.056	-0.029
	(0.524)	(0.520)	(0.521)	(0.524)
Ln(Past Amount Invested)	0.001			
	(0.048)			
Ln(Past Firms Invested)		-0.007		
		(0.076)		
Ln(Past Fund Raised)			-0.066**	
			(0.032)	
Ln(VC Age)				-0.008
				(0.090)
Controls, industry and year fixed effects	Yes	Yes	Yes	Yes
Lead VC fixed effects	Yes	Yes	Yes	Yes
Observations	12,102	12,102	12,102	12,065
R^2	0.456	0.456	0.457	0.456

Dependent Variable: Ln(Citations/Patent)	(1)	(2)	(3)	(4)
Ln(Failure Tolerance)	0.758***	0.793***	0.758***	0.750***
	(0.163)	(0.164)	(0.141)	(0.163)
Investment Concentration	-0.565	-0.641*	-0.612*	-0.463
	(0.353)	(0.352)	(0.327)	(0.327)
Past IPO Exit	0.269	0.204	0.270	0.219
	(0.465)	(0.459)	(0.455)	(0.465)
Ln(Past Amount Invested)	-0.052			
	(0.039)			
Ln(Past Firms Invested)		-0.105*		
		(0.061)		
Ln(Past Fund Raised)			-0.083***	
			(0.028)	
Ln(VC Age)				-0.101
				(0.079)
Controls, industry and year fixed effects	Yes	Yes	Yes	Yes
Lead VC fixed effects	Yes	Yes	Yes	Yes
Observations	12,102	12,102	12,102	12,065
R^2	0.352	0.352	0.353	0.352

Table 5: Orthogonalized VC Failure Tolerance

Panel A: Determinants of Investment Duration in Failed Projects

The dependent variable is the natural logarithm of a VC firm's failure tolerance in a given year. Portfolio firm industry fixed effects refer to the industry a VC firm invests in. 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. This analysis is based on a sample that contains the entire investment history of the 638 lead VC firms that appear in our IPO sample. 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.

	(1)	(2)	(3)	(4)
Ln(Past Amount Invested)	0.055***			
	(0.006)			
Ln(Past Firms Invested)		0.061***		
		(0.010)		
Ln(Past Fund Raised)			0.021***	
			(0.003)	
Ln(VC Age)				0.124***
				(0.012)
Investment Concentration	0.035***	0.025**	0.012	-0.006
	(0.012)	(0.012)	(0.012)	(0.011)
Past IPO Exit (%)	-0.058	-0.038	-0.042	0.014
	(0.040)	(0.040)	(0.039)	(0.038)
Constant	0.699***	0.726***	0.808***	0.593***
	(0.140)	(0.145)	(0.140)	(0.152)
VC firm fixed effects	Yes	Yes	Yes	Yes
Portfolio firm industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	7,281	7,281	7,281	7,214
R^2	0.782	0.779	0.779	0.790

Panel B: Effect of Orthogonalized VC Failure Tolerance

"Orthogonalized Ln(Failure Tolerance)" is the residual term from each regression in Panel A. The model numbers correspond to those in Panel A. For example, the orthogonalized failure tolerance measure in model (1) is the residual term from regression (1) in Panel A. The observation unit in this analysis is IPO firm-year. The standard errors of the coefficient estimates for the generated variables have been corrected. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

Dependent Variable: Ln(Patents)	(1)	(2)	(3)	(4)
Orthogonalized Ln(Failure Tolerance)	0.392***	0.437***	0.553***	0.509***
	(0.075)	(0.070)	(0.063)	(0.058)
IPO firm controls	Yes	Yes	Yes	Yes
Industry and year fixed effects	Yes	Yes	Yes	Yes
Observations	12,102	12,102	12,102	12,065
R^2	0.317	0.318	0.320	0.319

Dependent Variable: Ln(Citations/Patent)	(1)	(2)	(3)	(4)
Orthogonalized Ln(Failure Tolerance)	0.459***	0.494***	0.548***	0.532***
	(0.063)	(0.071)	(0.054)	(0.069)
IPO firm controls	Yes	Yes	Yes	Yes
Industry and year fixed effects	Yes	Yes	Yes	Yes
Observations	12,102	12,102	12,102	12,065
R^2	0.256	0.257	0.258	0.258

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)	1.951***	0.683***	1.889***	0.652***
	(0.570)	(0.180)	(0.383)	(0.156)
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	2,301	9,801	2,301	9,801
R^2	0.562	0.466	0.426	0.364

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)	1.058***	0.513*	1.035***	0.454*
	(0.264)	(0.293)	(0.194)	(0.254)
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	7,557	4,545	7,557	4,545
R^2	0.489	0.531	0.383	0.395

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)	1.695***	1.015***	0.714**	0.758
	(0.433)	(0.372)	(0.282)	(0.817)
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	2862	3,194	2,914	955
R^2	0.441	0.531	0.370	0.720

Panel B: Patent Impact

Dependent Variable: Ln(Citations/Patent)	Drugs & Chemical (1)	Computers & Electrical (2)	Software (3)	Low-Tech (4)
Ln(Failure Tolerance)	1.233***	1.233***	0.654***	0.415
	(0.313)	(0.344)	(0.253)	(0.714)
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	2862	3,194	2,914	955
R^2	0.431	0.389	0.273	0.719