# TOLERANCE FOR FAILURE AND CORPORATE INNOVATION

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## Abstract

We examine whether tolerance for failure spurs corporate innovation based on a sample of venture capital (VC) backed IPO firms. We develop a novel measure of VC investors' failure tolerance. 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 being financed by a failure-tolerant VC is much more important for ventures with high innovation potentials than for those with low potentials. We also find that the effect of failure tolerance on innovation persists long after VC investors exit the IPO firms, and the effect is even more persistent if the startup firms start to interact with the VCs in the firms' early development stages. Such persistence suggests that VC investors' attitudes towards failure have likely been internalized by the startup firms and become part of the firms' culture.

## 1. INTRODUCTION

Innovation is vital for the long-run comparative advantage of firms. However, motivating innovation remains a challenge for most firms because innovation activities are inherently different from standard tasks such as manufacturing and marketing. 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. Failure in this context means that in the process of developing a new technology/product, efforts exerted by the firm yield no desirable outcome. The recent theoretical literature on corporate innovation argues that tolerance for failure is critical in motivating innovation, and standard incentive schemes such as pay-for-performance can fail to do so (e.g., Hellmann and Thiele 2009, Manso 2008). However, there has been little empirical evidence in this area largely because measuring failure tolerance in a firm is difficult.

In this paper we adopt a novel empirical approach to examine the effect of failure tolerance on a firm's innovation productivity. 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 because these firms generally have both high innovation potential and high failure risk.

VC investors' tolerance for failure may affect the innovation productivity of VC-backed startup firms through both a direct effect and an indirect but more enduring effect. The direct effect is that VC investors' tolerance for failure prevents premature liquidation upon difficulties in the early development stages and allows entrepreneurial firms to realize their innovation potentials. The indirect effect is that VC investors' attitudes towards failure may have a profound impact on the formation of a failure-tolerant culture in the entrepreneurial firm, which in turn can have a persistent effect on the firm's innovation productivity. Both effects are possible because VC investors not only provide capital but also interact intensively with the startup firms often from the very beginning stages to the firms' maturity. Through such intensive involvement, failure-tolerant VC investors may not only directly help with the innovation process but also influence the shared beliefs and attitudes about failure in the startup firms.

We infer a VC firm's failure tolerance by examining its tendency to continue investing in a project conditional on the project not meeting milestones. Specifically, failure tolerance is captured by the VC firm's average investment duration (and the number of financing rounds) in its past failed projects from the first investment round to the termination of follow-on investments. 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. If a project does not show progress towards stage targets, 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 examine how a VC firm's failure tolerance is correlated with its other characteristics. We find that VC firms with more past investment experiences, fewer liquidity constraints, and more industry expertise are more tolerant of early failures in projects. However, a VC firm's past successful experience does not significantly impact its failure tolerance.

We then link a VC investor's failure tolerance to IPO firms backed by the VC investor. An IPO firm's failure tolerance is determined by its investing 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), after controlling for firm and industry characteristics. The results are robust to alternative measures of failure tolerance and alternative empirical and econometric specifications.

Although the baseline results are consistent with VC investors' failure tolerance leading to higher ex-post innovation productivity in VC-backed startup firms, an alternative interpretation of the results could be that failure-tolerant VCs are in equilibrium matched with firms that have high ex-ante innovation potentials, and high ex-ante potentials lead to high ex-post outcomes. We thus conduct a rich set of analysis to address this possibility.

First, we show that the failure tolerance effect on innovation is robust to controlling for the endogenous matching between failure-tolerant VC investors and startup firms. Specifically, we control for a VC investor's characteristics that are correlated with both its tolerance for failure and its project selection ability. We also control for project characteristics that may reflect a project's ex-ante innovation potential and failure risk. We control for these VC firm and project characteristics in different ways: as control variables and as conditioning variables. In sum, we find that the failure tolerance effect cannot be explained by VCs' abilities to select better projects based on their past investment experiences and industry expertise. Nor can the effect be explained by the tendency of failure-tolerant VCs to invest in industries or projects with high ex-ante innovation potentials and also high failure risk.

Second, we show that conditional on a startup firm having a high ex-ante innovation potential, VCs' failure tolerance is still necessary for the firm to achieve high ex-post innovation productivity. In fact, VCs' tolerance for failure is much more important for ventures with high potentials and high failure risk than for ventures with low potentials and low failure risk.

For instance, the VC literature suggests that startups that receive the first-round VC financing in their early development stages (hereafter early-stage ventures) tend to be more innovative, but the failure risk is typically the highest at the early stages. We find that among the early-stage ventures, being financed by a more failure-tolerant VC is associated with significantly higher ex-post innovation productivity. But among the late-stage ventures that on average have lower potentials and lower failure risk, VCs' failure tolerance is not important at all for innovation. For another instance, we find that the effect of failure tolerance on firm innovation is the strongest in industries with high rewards for innovation but also high failure risk (e.g., the pharmaceutical and the medical devices industries). These results imply that a high ex-ante potential does not automatically lead to a high ex-post outcome. VCs' tolerance for failure helps startup firms to realize their innovation potentials.

After addressing the endogeneity issue, we go further to investigate the persistence of the failure tolerance effect on startups' innovation. We find that the failure tolerance effect on innovation persists long after VC firms exit their investments in the IPO firms. More interestingly, the effect is even more persistent if an entrepreneurial firm starts to interact with VC investors in the beginning stages of development when the firm's culture is immature. These results suggest that the failure tolerance effect reflects not just a direct and temporary VC firm influence while the VC investors are present in the startup firm, but also a more persistent cultural effect. That is, the VC investors' attitudes towards failure have likely been internalized by the startup firm and become part of the firm's culture.

Finally, in extensions to our main analysis we find that opposite to the effect of failure tolerance, standard incentive schemes such as insider equity ownership are negatively associated with startup firms' innovation productivity. Although we do not claim a causal effect of insider equity ownership, this finding is consistent with the theoretical implications that motivating innovation is very different from motivating efforts on standard activities such as production and marketing. We also find that failure tolerance increases the value of VC-backed IPO firms in industries in which innovation is important, but does not contribute to firm value in industries in which innovation is not relevant.

Our paper contributes to the literature on corporate innovation by providing new evidence on the theoretical implications about motivating innovation. We discuss the relevant theories on innovation in detail in Section 2. There is also a growing empirical literature in corporate finance on innovation. Several papers show that the legal system matters for innovation (e.g., Acharya and Subramanian 2009 on the effect of a creditor-friendly bankruptcy code, Armour and Cumming 2008 on "forgiving" personal bankruptcy laws, Acharya, Baghai-Wadji, and Subramanian 2009 on the effect of stringent labor laws, and Sapra, Subramanian, and Subramanian 2009 on the effect of anti-takeover laws). Another set of papers find that ownership structure and financing matter for innovation (e.g., Aghion, Van Reenen, and Zingales 2009 on the role of institutional equity ownership, Belenzon and Berkovitz 2007 and Seru 2008 on the effect of internal capital market, and Atannassov, Nanda, and Seru 2007 on the effects of arm's length financing versus relationship-based bank financing). Our paper contributes to this literature by documenting the effect of failure tolerance on firm innovation.

Our paper also contributes to the literature on corporate culture. This literature remains mainly theoretical because corporate culture is difficult to define or measure in empirical analysis. The only other empirical paper we are aware of that is related to corporate culture is Cronqvist, Low, and Nilsson (2009). The authors find that spin-off firms' investment and financing decisions are similar to those of their parent firms, and such similarity persists over a long period. The authors argue that such persistence is consistent with a corporate culture effect. While Cronqvist et al. identify the corporate culture effect by examining the role of a common firm origin between spin-off firms and their parent firms in their decision-making, we show that the first-generation insiders' tolerance for failure has a significant and long-lasting impact on the firm's innovation productivity.

Finally, our paper contributes to the literature on VC investors' role in firm value creation. This literature has shown that VC investors' experiences, industry expertise, reputation, market timing ability, and network positions can all increase the value of VC-backed startup firms (see Gompers 2006 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 are associated with significantly more innovations. Our paper shows that the variation among VC investors in terms of their tolerance for failure is important to explain the heterogeneity in the observed innovation productivity of VC-backed firms.

The rest of the paper is organized as follows. Section 2 develops the hypothesis. Section 3 discusses the construction of the failure tolerance measure. Section 4 describes the empirical specification. Section 5 reports the results regarding the effects of failure tolerance on firm innovation and addresses identification issues. Section 6 presents some extensions to the main analysis. Section 7 concludes.

## 2. HYPOTHESIS DEVELOPMENT

We derive our hypothesis from the recent theoretical literature on motivating innovation. Holmstrom (1989), in a simple principle-agent model, shows that innovation activities may mix poorly with relatively routine activities in an organization because these two types of activities require different incentive schemes. Innovation activity requires exceptional tolerance for failure and a weak incentive scheme because of the high-risk and low-predictability nature of innovation.

Manso (2008) explicitly models the innovation process and the trade-off between exploration of new untested actions and exploitation of well known actions. Manso shows that while standard pay-for-performance incentive scheme can motivate exploitation, 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. Ederer and Manso (2009) conduct a controlled laboratory experiment and provide evidence supporting the implications in Manso (2008).

While Manso (2008) assumes contractibility of innovation activities, Hellmann and Thiele (2009) argue that innovative tasks are better characterized by incomplete contracts and ex-post bargaining (also see Aghion and Tirole 1994). The authors focus on the interaction between standard tasks and innovation in a multi-task model in which employees choose between the two types of activities. They show that the amount of innovation is negatively related to the strength of incentives provided for the standard tasks. The optimal amount of failure tolerance also reflects the trade-off between the two types of tasks: failure tolerance can encourage innovation, but can also undermine incentives for standard tasks.

The essential message from the above theories is that motivating innovation is very different from motivating efforts on standard tasks. Tolerance for failure is critical in motivating innovation. These insights form the theoretical foundation of our empirical analysis. Our main hypothesis is summarized below.

**Hypothesis:** *Tolerance for failure increases a firm's innovation productivity.*

With the hypothesis in hand, we turn to the specifics of the empirical research design.

## 3. FAILURE TOLERANCE

### 3.1 The Idea

To examine the effect of failure tolerance on a firm's innovation productivity, we start with VC investors' attitude towards failure and investigate how such attitude affects innovation in VC-backed startup firms. VC-backed firms provide an ideal research setting for this study. Entrepreneurial firms receiving VC financing are typically highly innovative with high growth potential but also significant failure risk (e.g., Hellmann and Puri 2000). This means that both tolerance for failure and innovation are very relevant for this group of firms.

How does VC investors' tolerance for failure affect the innovation productivity in VC-backed venture firms? We believe that there can be both a direct effect and an indirect but more enduring effect.

The direct effect arises from the fact that VC investors are not only financers but also monitors of an entrepreneurial firm. They typically sit on the firm's board and have the final decision power on whether to continue investment or to abandon the project. If the VC investors are not tolerant of failure, then the ventures are likely to be liquidated prematurely upon initial negative information and therefore lose the chance to be innovative.

The indirect effect is that VC investors' attitude towards failure can have a profound impact on the formation of a failure-tolerant corporate culture in the startup firm. Such culture in turn can have a persistent effect on the firm's innovation productivity, even after VC investors exit their investment and lose their control power in the firm.

Corporate culture is essentially shared beliefs and organizational preferences among a firm's employees about the optimal course of action (see, e.g., Kreps 1990, Cremer 1993, Lazear 1995, and Hermalin 2001). As Edgar Schein points out, the process of culture formation in an organization begins with the founding of the group. "Culture is created by shared experience, but it is the leader who initiates this process by imposing his or her beliefs, values and assumptions at the outset" (Schein 2004). Thus the formation of a corporate culture is largely determined by the beliefs and values of its first-generation leaders—founders and early active investors.

VC investors are early active investors in a startup firm. They not only provide capital but also interact intensively with the entrepreneurs.[1] Through such active interactions, VC investors may influence the formation of shared beliefs and values in the venture firm. Given the high-failure-risk nature of VC-backed ventures, attitude towards failure is one important aspect of corporate culture that VC investors can potentially influence on. If the VC investor is tolerant of initial failure and willing to give the entrepreneurs a second chance when the firm fails to meet stage targets, then such tolerance is likely to be much appreciated and valued by the entrepreneurs who eventually succeed after struggling with and overcoming the early failures in their innovation journey. These entrepreneurs are also likely to be more tolerant of early failures in future innovation activities in the firm. Therefore, entrepreneurial firms backed by failure-tolerant VC investors are more likely to develop a failure-tolerant culture.

In sum, our intuition is that VC investors' attitude towards failure may not only directly affect the innovation outcome in an entrepreneurial firm, but also be "inherited" or internalized by the entrepreneurs and become a part of the entrepreneurial firm's culture, which in turn affects the firm's subsequent innovation activities and performance.

### 3.2 VC Firm's Failure Tolerance

Failure in this study means unsatisfactory outcomes in the innovation process. We try 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. This is why the staging of capital infusions is an essential feature of VC investments. Staging allows VC investors to gather information and monitor the project progress.

[1] See, e.g., Sahlman 1990, Gompers 1995, Lerner 1995, Hellmann and Puri 2000 and 2002, Chemmanur and Loutskina 2006, and Bottazzi, Da Rin, and Hellmann 2008.

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, 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 early failure in investments.

A challenge for us is to empirically capture "conditional on the project not meeting stage targets". The available VC investment data provide the information about the outcome of each round of evaluation (i.e., continued investment or termination of funding), but not the conditioning information (e.g., whether the project meets the stage targets). If a project's eventual outcome is successful, then researchers cannot tell whether the project has struggled through early difficulties or it has sailed smoothly through the entire process. But if the ultimate outcome of the project is unsuccessful, the project probably has not met stage targets even before the VC investor makes the liquidation decision. Thus, for the eventually failed projects the option to abandon is likely to be relevant at each round of evaluation.

We construct the measure of a VC firm's failure tolerance based on a sample of failed investments the VC investor made in the past. Failure tolerance measures how long a VC firm on average waits before terminating its follow-on investments in projects that eventually failed. 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). The investment duration in a project is the time interval (in years) between the first capital infusion from VC firm-$i$ to the termination of funding by VC firm-$i$. Failed projects are those that are eventually written off by their investing VC investors. 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 failed projects accumulates over time, the failure tolerance measure is time-varying, allowing the VC investors' attitude towards failure to slowly change over time.[2]

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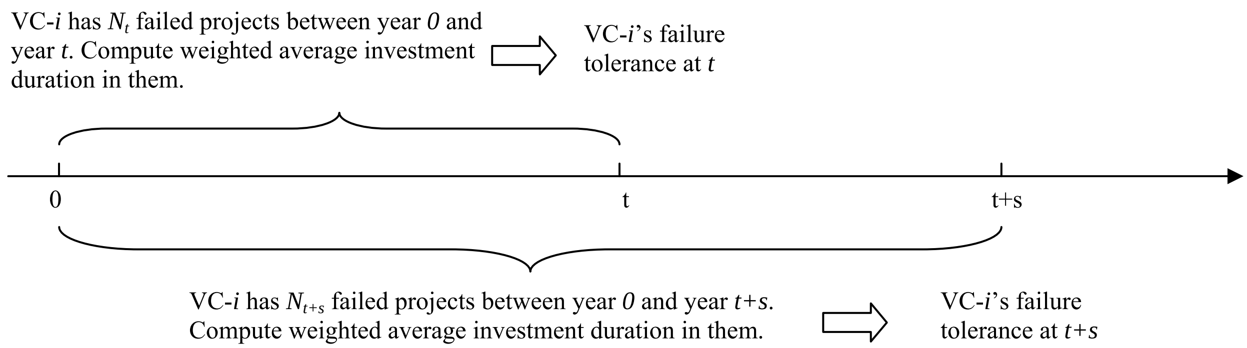
[2] A subtle but relevant concern is whether our measure is capturing a VC's attitude towards risk or attitude towards failure. Tolerance for risk is an investor's *ex-ante* attitude towards uncertainties of investment outcomes, while tolerance for failure measures how an investor *ex post* reacts to 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, venture capital

Figure 1: VC Firm's Failure Tolerance




Of course the investment duration in failed projects can be affected by factors other than a VC's tolerance for failure. For example, the investment cycle may be different in different industries, driving the variation in the average investment duration. For the main analysis we choose not to adjust for industry effects directly in the failure tolerance measure, but to control for them in the regression analysis because all our variables of interest (e.g., innovation) are subject to industry effects. We do construct an industry-adjusted failure tolerance for robustness tests (Section 5.2). We also conduct industry-by-industry analysis (Section 5.3.2).

A VC firm's experience, capital constraints, and diversification concerns may also affect the investment duration. We will examine the correlation of our failure tolerance measure with these factors in the next section. We will also show that the failure tolerance effect is distinct from the effects of these correlated VC characteristics.

Our intuition for measuring failure tolerance by the average investment duration in failed projects suggests that using the number of financing rounds the VC firm makes before writing off an under-performing venture may work as well. Intuitively, the investment duration and the number of financing rounds in a failed project should be highly correlated. Thus for robustness we construct an alternative measure of failure tolerance based on the weighted average number of financing rounds a VC firm made in its past failed projects.

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

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 VC industry in the first place. Second, our VC failure tolerance measure is built on the VC investor's past failed investments that probably have underperformed even before liquidation. Therefore, how long a VC investor waits before writing off the project reflects his *ex-post* reaction to an unsuccessful outcome rather than his *ex-ante* willingness to accept high uncertainty in the investment outcomes.

2006.[3] Appendix A point A discusses the details of the data cleaning. To construct the VC failure tolerance measure, we focus on the sub-sample of 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 10 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 10-year span after its very last financing round.

There are 18,546 eventually failed entrepreneurial firms 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. The weight is the VC firm's investment in a project as a fraction of its total investment up to that year. We compute the alternative failure tolerance measure based on the number of financing rounds, *Failure Tolerance 2,* in a similar fashion.

Table 1 provides the descriptive statistics for the VC failure tolerance variables. There are 18,993 VC firm-year observations with the failure tolerance information available in our sample. On average, VC investors invest for about 1.4 years, or make about two rounds of financing, before terminating funding in an unpromising project. The correlation between the two failure tolerance measures is 0.63.

The distribution of *Failure Tolerance* is right skewed with skewness of 2.43. Also, from an economic perspective there is a large difference between waiting for two years rather than one

[3] 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.

year before terminating an investment, but probably a smaller difference between waiting for ten years versus nine years. Both the skewness and the likely nonlinearity in the economic impact of VC's tolerance for failure suggest that a logarithm transformation of the failure tolerance measure is appropriate. We then use the natural logarithm of *Failure Tolerance* as the main measure in the rest of the analysis.

### 3.3 Failure Tolerance and VC Firm Experience

A possible concern is that our failure tolerance measure may simply measure a VC firm's inability to efficiently terminate unpromising projects. Experienced VC investors terminate unpromising projects earlier and less sophisticated ones wait for too long. Thus in this section we examine how a VC firm's failure tolerance is correlated with its experience. We examine VC experience from three different angles: past general investment experience, past successful experience, and industry expertise. If the failure tolerance measure captures a VC's inexperience, then we expect a negative relationship between failure tolerance and VC investment experience.

For each 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*). Note that these VC experience measures, especially the past fund raised, may also capture the degree of capital constraint the VC firm faces.

It is also possible that a VC's attitude towards failure is related to its past successful experience as well as its overall investment experience. Thus for each VC firm and each year, we compute *Past Successful Exit* as the proportion of entrepreneurial firms financed by the VC firm that exited successfully through either going public or acquisition since 1980. Previous literature also 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 calculate *Past IPO Exit* as the fraction of entrepreneurial firms financed by the VC firm that went 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. 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 $\overline{w}_{t,j}$ : $\sum_{j=1}^{18}(w_{i,t,j} - \overline{w}_{t,j})^2$. 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 shows that the average VC firm in a given year is 8.6 years old and has invested 395 million dollars in 24 entrepreneurial firms. Among all firms the average VC firm has financed, 53% had a successful exit but only 16% went public. The average VC's portfolio firms are concentrated in a few industries with the investment concentration index of 0.37.

Table 2 reports the panel regression results with *Ln(Failure Tolerance)* as the dependent variable. In all regressions, we include VC firm fixed effects and year fixed effects. To control for potential differences in investment cycles in different industries, we also control for the entrepreneurial firms' industry fixed effects based on the 18-industry classification in Venture Economics.[4] Since the four VC investment experience variables are highly correlated with each other, we include them one by one in the regressions.

In all four models the coefficient estimates of VC investment experience proxies are positive and significant. This suggests that as a VC firm becomes more experienced over time, it also becomes more failure tolerant. The positive coefficient estimate of *Past Fund Raised* may also be interpreted as suggesting that good fund raising reduces the VC firm's liquidity constraint so that it can afford to be more tolerant of early failures in the startup firms. The coefficient estimate of a VC firm's investment concentration is positive in all models and is significant in three out of four models. This suggests that as a VC firm becomes more specialized over time, it

[4] 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.

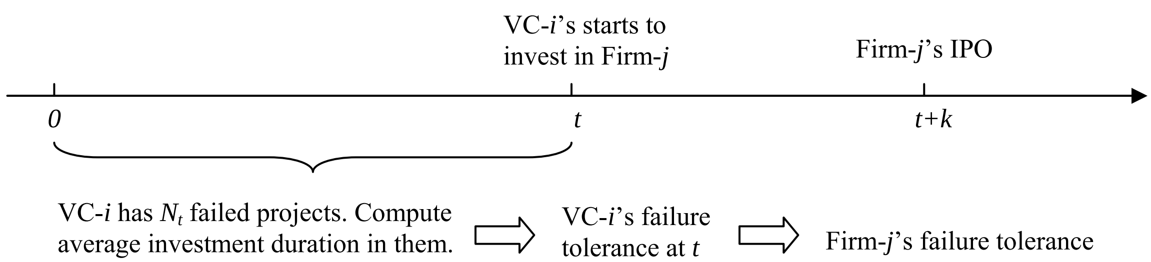
also becomes more tolerant of early failures in their portfolio firms. Lastly, the coefficient estimate of a VC's past successful exit rate is generally positive and statistically insignificant. We find similar results when replacing the VC's past successful exit rate with its past IPO exit rate. This implies that after controlling for VC's investment experience and expertise, the VC's attitude towards failure is independent of its past successful experience.

In sum, we find that more experienced VCs are more failure tolerant. This suggests that the failure tolerance measure is unlikely to capture a VC firm's inability to efficiently terminate unpromising projects.

### 3.4 IPO Firm's Failure Tolerance

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

Figure 2: IPO Firm's Failure Tolerance




We obtain the list of VC-backed IPOs between 1985 and 2006 from the Securities Data Company (SDC) Global New Issues database.[5] We utilize 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.

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[5] 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 in which the *Failure Tolerance* measure is constructed and the beginning year of our IPO sample in which the *Failure Tolerance* measure is utilized. By doing so, we minimize the possibility that the VC-backed IPO firm has no *Failure Tolerance* information available.

For each IPO firm in our sample, we observe the identity of its investing VC firms, the value of each VC firm's *Failure Tolerance* measure, and other VC characteristics as reported in Table 1 at their first participation round dates. If an IPO firm receives funding from a VC syndicate (about 86% of our sample), we then calculate the weighted-average of the VCs' *Failure Tolerance* measures. The weight is the investment by a VC firm as a fraction of the total VC investment received by the IPO firm. Consequently, there is a fixed failure tolerance measure for each IPO firm in our final sample. Panel A of Table 3 reports the descriptive statistics of the IPO firms' *Failure Tolerance* measure. The mean *Failure Tolerance* is about one year and ten months and it could be as large as six years and four months.

For each IPO firm we also calculate the weighted-average of VC characteristics including past investment experience, past successful experience, and investment concentration. All these VC characteristics are parallel to our IPO firm failure tolerance measure by construction. Table 3 Panel A shows that compared with the summary statistics of all VC firms that have financed failed projects as reported in Table 1, the VC investors of our IPO sample are older, have invested more money and in more firms, have raised more funds, have a more diversified investment portfolio, and have more successful past investment experience.

Table 3 Panel B shows the industry distribution of the IPO firms with failure tolerance above/below the IPO sample median. Overall, the industry composition is not significantly different between firms backed by more failure-tolerant VCs and those backed by less failure-tolerant VCs. This suggests that the differences in IPO firms' failure tolerance are unlikely to be driven by industry effects.

We extract financial information for the IPO firms from Standard & Poor's COMPUSTAT files, stock prices and shares outstanding data from CRSP, insider ownership from the Compact Disclosure database, 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.

## 4. EMPIRICAL SPECIFICATION

To examine how failure tolerance affects the firm's innovation productivity after IPO, we estimate the following empirical model:

$$Ln(Innovation_{i,t}) = \alpha_0 + \beta \times Ln(FailureTolerance_i) + \delta Z_{i,t} + Ind_j + Year_t + u_{i,t} \qquad (1)$$

The construction of *Innovation* is discussed in detail in Sections 4.1. *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 *Failure Tolerance* in our study is a time-invariant firm characteristic, the panel data regression as specified above tends to downward 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 the Fama-Macbeth method and run regressions year by year.

An advantage of our empirical design is that the main variable of interest, *Failure Tolerance,* is least subject to reverse causality concerns. This is because *Failure Tolerance* captures the investing VC firm's attitude towards failure before its very first investment round in an IPO firm, which happens well before we observe the innovation activities of the IPO firm.

### 4.1 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 then 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, we construct the second measure that intends to capture the importance of each patent 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 their returns from innovations. However, there is no clear reason to believe that such noise, which is in the regression error term in (1), is systematically correlated with the failure tolerance measure. Further, Cohen, Nelson, and Walsh (2000) show that firms across industries view patenting as one of the most effective ways to protect profits from their innovations.

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. Panel C of Table 3 presents the IPO firm-year summary statistics of the innovation variables. As shown in the table, the distribution of patent grants in the full IPO sample is right skewed. Firm-year observations with zero patent represent roughly 73% of the sample. But this percentage is still significantly lower than that reported in Atanassov, Nanda, and Seru (2007) (84%) whose sample includes the universe of COMPUSTAT firms. This suggests that VC-backed IPO firms are on average more innovative than firms represented by the COMPUSTAT universe. On average, an IPO firm has 3.11 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 then use the natural logarithms of patent counts and citations per patent as the main innovation measures in our analysis.[6]

### 4.2 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

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

(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.

All the financial variables in the analysis are winsorized at the 1st and 99th percentiles to mitigate the influence of outliers on the results. Panel D of Table 3 reports the summary statistics of IPO firm characteristics. In our IPO sample, $Q$ ranges from 0.58 to 19.44 with a mean value of 3.01 and a standard deviation of 2.94. The average firm has total book assets of 485.5 million dollars, sales of 375 million dollars, leverage of 34.6%, and net PPE ratio of 17.36%.

## 5. FAILURE TOLERANCE AND CORPORATE INNOVATION

### 5.1 Baseline Results

Table 4 reports the baseline results on how failure tolerance affects a 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 4 shows that IPO firms backed by more failure-tolerant VCs tend to produce more patents. The elasticity of patents to *Failure Tolerance* is 0.258. This means that a one percent increase in *Failure Tolerance* on average leads to more than a quarter 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 3 Panel A, this VC firm on average invests for 1.3 years in past failed projects before terminating funding. If this VC firm is willing to invest for 2.3 years before giving up a project (roughly the 75th percentile of the failure tolerance distribution), then everything else equal the IPO firms backed by this VC firm tend to have 20% ($= \frac{2.3-1.3}{1.3} * 0.258$) more patents per year later on.

In model (2) we restrict the analysis to firms with at least one patent during the sample period (1985-2006).[7] We expect the effect of failure tolerance to be stronger in this subsample of firms for which innovation is absolutely relevant. This is exactly what we find. The elasticity of

[7] The number of observations in Table 4 model 2 is 7,607, while it is 5,264 in Table 3 Panel B for the subsample with patents>0. The discrepancy is due to a difference in the definition of subsample with patents>0. In Table 4 model 2, "Patents>0" means that the firm has at least one patent over the entire sample period (but not necessarily in every year). In Table 3 Panel B, "Patents>0" means that the patent count is non-zero for a firm-year observation.

patents to failure tolerance increases to 0.422 in this subsample and is even more statistically significant.

Models (3) and (4) of Table 4 show that firms backed by more failure-tolerant VCs also tend to produce patents of higher impact. Model (3) shows that a one percent increase in failure tolerance on average leads to a 0.2 percent increase in citations per patent. Again, the effect of failure tolerance is much stronger in the subsample of firms with nonzero patents. 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), 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. Higher investment (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, firm age, 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 tolerance for failure can increase a firm's innovation productivity. These results provide support for the implications of Holmstrom (1989) and Manso (2008) that tolerance for failure is critical in motivating innovation.

### 5.2 Robustness

We conduct a set of robustness tests for our baseline results on alternative econometric specifications. Besides the pooled OLS specification reported in Table 4, we use the Fama-MacBeth regression adjusting for auto-correlations of coefficient estimates and get an even stronger estimate for the failure tolerance effect. We also use a Tobit model that takes into consideration the non-negative nature of patent data and citation data. We run a Poisson regression when the dependent variable is the number of patents to take care of the discrete

[8] For example, the coefficient estimate of Ln(Failure Tolerance) is 0.238 (p-value=0.03) in model (3) of Table 4 when the natural logarithm of the modified citations per patent is the dependent variable.

nature of patent counts. We run a firm random-effect model, which is generally more efficient than a pooled OLS regression (Wooldridge 2009, page 493). 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 1994a). 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 a VC investor made in its past failed projects. For example, the coefficient estimate for *Ln(Failure Tolerance 2)* in model (1) of Table 4 is 0.368 (p-value = 0.007), and is 0.305 (p-value = 0.006) in model (3).

In all regressions we control for industry fixed effects. For further robustness, we construct an industry-adjusted failure tolerance measure. Specifically, for a project in industry-*j* that failed in year *t*, we subtract from the project's investment duration the median investment duration of all failed projects in the same industry up to year *t*. The industry classification is based on the 18-industry classification in Venture Economics. We then use the adjusted project investment duration to compute the failure tolerance of a VC. In the baseline regressions, we regress the industry-adjusted innovation productivity on the industry-adjusted failure tolerance as well as the industry-adjusted contorl variables. The results are robust. The coefficient estimate for the industry-adjusted failure tolerance in model (1) of Table 4 is 0.116 (p-value = 0.019), and is 0.067 (p-value = 0.071) in model (3).

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 failure tolerance effect remains robust. For example, the estimated failure tolerance effect is 0.269 (p-value = 0.018) in model (1) of Table 4, and is 0.204 (p-value = 0.031) 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 very noisy. As a robustness check, we exclude IPO firms with investing VCs less than five years old (from the founding date). Our main results hold. For example, the estimated failure tolerance effect is 0.256 (p-value = 0.050) in model (1) of Table 4, and is 0.232 (p-value = 0.025) in model (3).

Lastly, we check whether the effect of failure tolerance on innovation is nonlinear. 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 in the full sample the impact of failure tolerance on patent counts is positive, but it turns to negative when the *Failure Tolerance* measure is greater than 2.45, which is at the top 16$^{th}$ percentile of the sample distribution. However, such nonlinearity disappears in the subsample of firms with at least one patent count. A similar pattern is observed when the dependent variable is patent citations. The evidence seems to suggest that the effect of failure tolerance on innovation productivity is positive and linear in firms in which innovation is pertinent.

### 5.3 Is It Really a Failure-Tolerance Effect?

Although our baseline results are consistent with VC investors' failure tolerance leading to higher ex-post innovation productivity in VC-backed startup firms, an alternative interpretation of the results could be that failure-tolerant VCs 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 try to address this alternative explanation as follows. First, we show that the failure tolerance effect on innovation is robust to controlling for the endogenous matching between VC investors and startup firms (sections *5.3.1-5.3.3*). Second, we show that conditional on firms having high ex-ante innovation potentials, VCs' failure tolerance is still necessary for achieving high ex-post innovation productivity. In other words, a high ex-ante potential does not automatically lead to a high ex-post outcome (section *5.3.4*).

#### *5.3.1 VC Firm Experience & Project Selection Ability*

Some VC firms may be better at selecting more innovative projects than others. Note that since we examine equilibrium matching outcomes, the same analysis applies irrespective of whether VCs select innovative firms or innovative firms select VCs. Thus for expositional ease, when we discuss selection ability, we describe it as selection by VC investors.

Sorensen (2007) shows that more experienced VCs invest in better projects. Recall that Table 2 shows that VC investors that are more experienced and more specialized in certain industries are more tolerant of failure. Then it is possible that more experienced VCs are more failure-tolerant and at the same time are better at selecting more innovative projects, driving the positive relationship between failure tolerance and innovation. If this were true, then we expect the effect of failure tolerance to disappear or substantially weaken after controlling for the VC firm's experiences and expertise.

In Table 5 we control for all the observable VC firm characteristics that proxy for investment experiences and expertise and are also correlated with the VC firm's failure tolerance as indicated by Table 2. They are *Investment Concentration*, *Past Successful Exit*, *Ln(Past Amount Invested)*, *Ln(Past Firms Invested)*, *Ln(Past Fund Raised)*, and *Ln(VC Age)*. As discussed in Section 3.4, all these characteristics are measured as of a VC's first investment in a startup firm, and thus we call them the VC's ex-ante characteristics. We also include a VC firm fixed effect to absorb the effect of any time-invariant unobservable VC firm characteristics. Since 86% of our IPO firms are financed by VC syndicates, we control for the lead VC firm fixed effects. The lead VC is defined as the one that invests the most in an IPO firm.[9] In all regressions we include all the control variables in the baseline regressions and industry and year fixed effects. To save space, we only report results for the key explanatory variables in the table.

Table 5 Panel A shows that after controlling for the investing VC firms' experiences and expertise, which should be positively correlated with their project selection ability, failure tolerance still has a positive and significant effect on patent generation and patent impact. The magnitude of the effect also remains stable relative to the baseline results. For example, the average elasticity of patents to failure tolerance in the four models is 0.27, which is comparable to the magnitude in model (1) of Table 4 (0.258). In addition, after controlling for the failure tolerance effect, none of the other VC firm characteristics significantly affects the innovation productivity of the IPO firms.

In Table 5 Panel B we further investigate whether the effect of failure tolerance on innovation differs across firms backed by VCs of different project selection abilities. Since a VC firm's selection ability is positively correlated with its past investment experience and industry expertise, we extract the principal-component factor of the six variables in Panel A that proxy for the VC's experiences and expertise. To facilitate the interpretation of the results, we rescale the principal-component factor so that it is between zero and one, and call it the *Selection Ability*. A higher value of this variable means a better selection ability. As expected, this variable is highly

[9] In our IPO sample, about 60% of the lead VC firms (based on our definition) had participated since the very first VC financing round received by the IPO firm, and about 90% of the lead VC firms started their investment in the first three VC financing rounds received by the IPO firm.

positively correlated with all the variables related to the VC's past investment experiences.

We then interact the failure tolerance measure with the selection ability measure. Table 5 Panel B shows that the direct effect of failure tolerance on innovation is still positive and significant. The interaction effect is negative, implying that the marginal impact of failure tolerance is weaker for firms backed by VC investors with higher selection abilities. However, this interaction effect is not statistically significant. We, therefore, cannot reject the null hypothesis that the failure tolerance effect is the same for startup firms financed by VC investors with different project selection abilities. Finally, the direct effect of the selection ability is positive, but only weakly significant for patent count and not significant for patent impact. This implies that a VC firm's ability to select projects that will later be highly innovative may be somewhat limited.

Taken together, the results in Table 5 suggest that the effect of VC firms' failure tolerance on innovation cannot be explained by VCs' abilities to ex-ante select innovative projects based on their past investment experiences and industry expertise.

*5.3.2 Selection by Industry*

Another possibility is that the omitted factors are ex-ante project characteristics rather than ex-ante VC firm characteristics. An important project characteristic is the project's industry membership. Different industries have different innovation potentials and also different degrees of failure risk. For example, the pharmaceutical/medical devices industries are known to have high failure risk but also high payoff for successful innovation. In such industries the value from "wait-and-see" is high, and thus the optimal level of failure tolerance is high. This implies that in equilibrium more failure-tolerant VCs are more likely to invest in industries with high failure risk and high innovation potentials, which may lead to a positive correlation between VC's failure tolerance and the startup firm's innovation productivity.

In all previous analysis we control for the industry fixed effects based on the SIC codes. In robustness tests, we also construct an industry-adjusted failure tolerance measure and show that the baseline results are robust to this modification (Section 5.2).

We believe that the cleanest way to control for the industry-level selection effect is to do an industry-by-industry analysis. We wish to achieve two goals with this analysis. First, we want to show that the within-industry variation in VCs' failure tolerance can explain the within-industry variation in startups' innovation productivity. The results from this analysis should not be driven by different types of VCs selecting into different industries. Second, if our failure tolerance measure indeed captures VCs' attitudes towards failure and if failure tolerance is important because innovation activities often involve substantial risk of failure, then a natural cross-sectional implication is that the effect of failure tolerance on innovation should be stronger in industries in which innovation is more difficult to achieve. The difficulty can come from a low probability of success and large resources demanded.

Here we use an alternative industry classification based on the technological nature of patents. Different types of patents involve different degrees of difficulty 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; (2) computers, communications, and electrical; (3) software programming; (4) other miscellaneous patents.[10] If a firm has no patent, then we classify it into one of the above four categories based on the type of patents that is most frequently produced by the firm's 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 the most difficult to produce. A new drug development process involves many steps requiring different levels of experimentation. Existing studies suggest that the cost of developing a new drug varies from $500 million to $2 billion (see, e.g., Adams and Brantner 2006). Hall, Jaffe, and Trajtemberg (2005) also show that the market value impact of drug patents is much higher than that of all other types of patents. Thus we expect tolerance for failure to be most important in industries producing new drugs.

Table 6 Panel A shows that compared to other patent categories, the drugs/medical equipments/chemicals industries (hereafter drugs industries) have the highest average VC failure

[10] 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 because we only have a few observations of chemical patents. Software programming patents (computer-related patents generated by the 3-digit SIC industry 737) belong to the computers and communications category. For finer comparisons between different types of patents, we single out software programming. We then group patents related to computer hardware, communications, and electrics together. Finally, we group metals, machinery and miscellaneous together because we do not have many observations of these patents and label this category as miscellaneous patents.

tolerance (1.88 years) and the lowest standard deviation of it (0.60 year). The differences relative to other categories are also statistically significant. This is consistent with the equilibrium matching between failure-tolerant VCs and industries with high failure risks.

Table 6 Panel B reports the baseline regressions for each patent category. In each category failure tolerance has a significantly positive effect on patent generation and patent impact. This means that the within-industry variation in VCs' failure tolerance can explain the within-industry variation in startup firms' ex-post innovation productivity.

Also as expected, the effect of failure tolerance on innovation is the strongest in drugs industries. For example, the elasticity of patents to failure tolerance is 0.743 in this patent category, almost triples the effect in the computers and electrical category (0.255), and almost quadruples the effect in the software programming category (0.190). As shown in the bottom rows of tables in Panel B, the differences in the failure tolerance effect between the drugs category and other categories are highly statistically significant.

In sum, the results in Table 6 suggest that the effect of failure tolerance on innovation is robust to controlling for the selection of different types of VCs into different industries. Also, the evidence that the failure tolerance effect is stronger in industries where innovation is more difficult to achieve provides powerful support for our empirical proxy of failure tolerance and the causal effect of failure tolerance on innovation.

### *5.3.3 Selection by Ex-Ante Project Characteristics*

Besides the industry membership, other finer ex-ante project characteristics may matter as well for the VC-startup matching. Again "ex-ante" means that the characteristics are measured at the time when a VC investor is matched with a startup firm. Failure-tolerant VCs may select projects with high innovation potentials but also high failure risk. Thus in this section we explicitly control for ex-ante project characteristics that may reflect a project's ex-ante innovation potential and failure risk.

Hellmann and Puri (2000) find that innovator firms are more likely to obtain venture capital earlier in the life cycle than do imitators. Thus firms that receive the first-round VC financing in their early development stage (hereafter early-stage ventures) are likely to have higher innovation potentials than those that receive VC financing in a late stage of development (hereafter late-stage ventures). The failure risk also varies in different stages of a startup firm's life cycle. In general, the probability of failure is the highest at the beginning stages of the firm. VCs that invest in early-stage ventures bear substantial failure risk. Thus more failure-tolerant VCs may be more willing to invest in early-stage ventures because they do not mind bearing the high failure risk that often accompanies the high potential.

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. 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. 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. Table 7 Panel A shows that VCs that invest in the early-stage ventures are indeed more failure-tolerant. The median failure tolerance is 1.79 for the early-stage ventures, and is 1.69 for the late-stage ventures. The difference between the two groups is statistically significant.

Our second ex-ante project characteristic is the number of investing VCs at the first-round investment (*# of VCs at 1$^{st}$-Round*). As suggested by the VC literature, projects with high quality and substantial risk tend to be funded by a large VC syndicate (e.g., Lerner 1994b). Thus we expect this variable to be positively correlated with a firm's ex-ante innovation potential and risk. Table 7 Panel A splits the sample into two groups based on the median of *# of VCs at 1$^{st}$-Round*. Projects with a larger first-round syndicate size tend to be matched with more failure-tolerant VCs than those with a smaller syndicate size, although the difference between the two groups is not significant.

The last ex-ante project characteristic is the *1st-Round Evaluation Interval*, which is the time interval between the first-round financing date and the second-round financing date. Since VCs conduct due diligence and evaluate the project progress before going into the next round, the investment duration of the first-round reflects the time to the first serious evaluation. The VC literature suggests that the more uncertainty in the project, the more frequent evaluations by VCs (e.g., Gompers 1995). Since innovation is a highly risky activity, we expect that the shorter the first-round evaluation interval, the more innovative and riskier the project. We believe that this is an ex-ante characteristic because the first serious evaluation date is typically specified in the initial contract between the VCs and the entrepreneurial firms (e.g., Kaplan and Stromberg 2003). Again Table 7 Panel A splits the sample into two groups based on the median of *1st-Round Evaluation Interval*. Projects with a shorter first-round evaluation interval tend to be matched with more failure-tolerant VCs than those with a longer evaluation interval, although the difference between the two groups is not significant.

Table 7 Panel B shows that after controlling for the ex-ante project characteristics as well as the ex-ante VC firms characteristics, failure tolerance still has a positive and significant effect on patent generation and patent impact. The average magnitude of the impact is also comparable to that in our baseline regressions. This implies that controlling for a firm's ex-ante innovation potential cannot explain the effect of failure tolerance on the firm's ex-post innovation outcome.

Table 7 Panel B also shows that early-stage ventures tend to be significantly more innovative ex post. This is consistent with the findings in Hellmann and Puri (2000) that more innovative firms are more likely to receive VC funding in earlier stages. The first-round VC syndicate size does not significantly impact the number of patents a firm generates ex post, but is significantly and positively related to the impact of the patents. This is consistent with our argument that better-quality projects attract a larger VC syndicate at the first-round. As expected, the logarithm of the first-round evaluation interval is negatively related to the innovation productivity. The effect is marginally significant in the patent count regressions, and is not significant in the patent impact regressions.

### *5.3.4 Development Stage of Venture and the Failure Tolerance Effect*

The findings in Hellmann and Puri (2000) and our findings in Table 7 suggest that early-stage ventures on average are more innovative than the late-stage ventures. Next, we wish to know that conditional on having projects with high ex-ante innovation potentials, whether VC's failure tolerance still matters for the ex-post outcome. Specifically, we examine the effect of failure tolerance on innovation conditional on the development stage of the venture when it receives the first-round VC financing.

In Table 8 we add the early-stage dummy variable and its interaction with failure tolerance to our baseline regression. The interaction term has a positive and significant effect on both patent counts and patent impact. The average failure tolerance effect on patent generation is 0.422 in early-stage ventures in model (1), which is much larger than the effect in the entire sample (0.258 in model (1) of Table 4). This implies that conditional on the firm being an early-stage venture, being financed by more failure-tolerant VCs leads to significantly higher ex-post innovation productivity.

The coefficient estimate of failure tolerance, however, becomes insignificant and even negative in the patent impact regression. This implies that VCs' tolerance for failure does not increase the innovation productivity in the late-stage ventures. Given that there is substantial variation in both the ex-post innovation outcomes and failure tolerance among the late-stage ventures, the insignificant failure tolerance effect on innovation in this group actually provides strong support for our empirical identification. If high failure tolerance simply proxies for high startup firm innovativeness, then we should expect the variation in failure tolerance to explain the variation in firms' ex-post innovation outcomes regardless of the stage in which they receive the first-round VC financing. However, this argument is not supported by our finding.

In addition, the coefficient estimate of *Early Stage* becomes insignificant. This suggests that having a high ex-ante innovation potential alone is not sufficient for achieving a high ex-post innovation outcome.

A coherent explanation for these results is as follows. VCs' failure tolerance matters a lot for early-stage ventures because these startups tend to have high innovation potential but also high failure risk. VC investors' tolerance for failure can help the ventures avoid being liquidated prematurely due to early failures and help them eventually realize their potentials. In late-stage ventures, however, the failure risk is substantially lower. Thus tolerating failure is less relevant for achieving high innovation productivity.

In sum, the analysis in sections 5.3.1-5.3.4 suggests that the effect of failure tolerance on innovation is robust to controlling for the endogenous matching between VCs and startups. Further, VCs' failure tolerance is particularly important for firms with high innovation potentials and high failure risk and in industries where innovation is difficult to achieve.

### 5.4 Persistence of the Failure Tolerance Effect

VC investors' beliefs and attitudes about failure are intangible values. These values will not stay in the venture firm unless they are internalized by the entrepreneurs. Once these values are internalized, they become part of the firm's culture. The economic theories suggest that a corporate culture, once formed, can persist over time, and have long-lasting effects on corporate decisions and performances (see e.g., Lazear 1995, Akerlof and Kranton 2000, 2005). Therefore, in this section we investigate the persistence of the failure tolerance effect. That is, for how long a period of time after IPO can the cross-sectional variation in firms' failure tolerance explain the cross-section variation in their innovation productivity?

Note that VC investors do not stay forever in the IPO firms they invest in. Existing studies show that VC investors on average cash out about 70% of their investment in an IPO firm within two years after the IPO (e.g., Gompers and Lerner 1998). In a sample of 339 VC-backed IPOs in Gompers (1996), the average duration of lead VC board representation in a venture is about three years (35 months) from its first-round investment. The average time from first-round VC investment to IPO date in our sample is 4.6 years. Thus VC investors are unlikely to exert their influence through board representation in a venture long after the firm goes public. If the VC investors' tolerance for failure is not internalized into the corporate culture of the entrepreneurial firm, then we expect the effect of failure tolerance to wane after the VC investors exit their investments. In this case, the failure tolerance effect we have documented simply reflects a transitory VC investor influence, not the effect of a corporate culture. As Hermalin (2001) puts it, corporate culture "resides with the firm, not an individual".

Our full sample panel regression analysis includes innovations generated long after a firm's IPO and after the exit of VC investments. In the Fama-Macbeth approach, we run year-by-year regressions and then take the average failure tolerance effect across years. This approach tells us whether the failure tolerance effect is stable over time. Both approaches give us a significant failure tolerance effect during the entire sample period, and thus provide some support for a persistent cultural effect.

To further check the persistence of the failure tolerance effect, in Table 9 we restrict the sample to firms that have existed for at least eight years after IPO. We then examine how the failure tolerance effect on innovation evolves within the first eight years after IPO.[11] The sample restriction mitigates the survivorship bias when we compare the effect over time.

We first examine the persistence of the failure tolerance effect on patent generation in Table 9 Panel A. We run year-by-year regressions of *Ln(Patents)* on *Ln(Failure Tolerance)* and

[11] We choose eight years as our cutoff for two reasons. First, if VC firms largely cash out of the IPO firms within two years after the IPOs as shown in Gompers and Lerner (1998), then we still have at least six years to examine the persistence of the failure tolerance effect. Second, this cutoff leaves us with a good sample size for the analysis. We have used other cutoffs such as five years and ten years, and results are consistent with those reported.

other control variables for the same set of firms. We then report the average of the coefficient estimate of *Ln(Failure Tolerance)* for firms with ages between one and two (age one being the IPO year), between three and five, and between six and eight, respectively. We also report the number of years with a significant estimate in each age group. We do not use the Fama-Macbeth regression for this exercise because the time series is too short in each age group and thus the standard error of the coefficient estimate cannot be precisely estimated. We report the average number of observations per year in each age group. The number is lower for the first age group because there are more observations with missing financial information in the IPO year (age = 1).

Since we run year-by-year regressions, a positive and significant failure tolerance effect in a number of consecutive years means that the cross-sectional variation in failure tolerance persistently explains the cross-sectional variation in innovation in that period of time.

The first half of Panel A reports the results for the entire sub-sample. The average failure tolerance effect is 0.451 in the IPO year and the year after, and the effect is significant in each year. This is the period when VC investors are cashing out of their investments. During the next three years (firm age between three and five), VC investors on average have already exited the IPO firms. But the failure tolerance effect stays strong (0.473) and significant. The effect starts to weaken in the sixth year. The average effect for age between six and eight is 0.327 and is insignificant. In sum, we find that the failure tolerance effect is strong in the first five years after IPO (including the IPO year), and the effect persists even after VC investors exit the firm.

Recall that Table 8 shows that the failure tolerance effect on innovation is much stronger in early-stage ventures. If the cultural effect is persistent and if VC investors are more likely to influence the culture of a startup firm by starting the interaction with the firm in its early development stages, then we expect to observe an even more persistent failure tolerance effect in early-stage ventures.

In the second half of Table 9 Panel A we single out the early-stage ventures in the sub-sample of firms included in the persistence analysis, and examine the failure tolerance effect over time. We find that the failure tolerance effect is not only much stronger but also much more persistent in the early-stage firms. The average failure tolerance effect is 0.672 in the first two years after IPO, increases to 0.859 during the next three years, and stays strong at 0.719 from the sixth to the eighth year after IPO. Throughout the eight-year window, the failure tolerance effect is statistically and economically significant for the early-stage firms. This implies that among early-stage ventures, being financed by a more failure-tolerant VC is associated with persistently higher innovation productivity.

Given that VC investors generally cash out of their investment within two years of a venture's IPO, the stronger persistence of the failure tolerance effect in the early-stage firms is difficult to be explained by the direct VC influence, but is more consistent with a cultural effect.

Table 9 Panel B reports the results for the number of citations per patent. We find that for the entire sub-sample the failure tolerance effect on patent impact is largely in the IPO year, and the effect quickly weakens after that. However, the effect is again much stronger and more persistent in early-stage ventures. The effect of failure tolerance on patent impact stays strong and significant in the first six years after IPO.

Overall, our analysis suggests that the failure tolerance effect on innovation persists long after VC firms exit the IPO firms. The effect is even more persistent if the entrepreneurial firms start to interact with the VC investors in early stages of the firms' life cycle. This implies that the failure tolerance effect we document does not simply reflect a transitory influence of VC firms. VC firms' attitudes towards failure have likely been internalized by the IPO firms they invest in.

## 6. EXTENSIONS

### 6.1 Standard Incentive Scheme versus Failure Tolerance

The economic theories suggest that although the standard incentive scheme such as pay-for-performance is effective at motivating efforts on standard tasks, it can fail to motivate innovation (e.g., Manso 2008, Hellmann and Thiele 2009). In Table 10 we compare the role of the standard incentive scheme with that of failure tolerance in motivating innovation.

In the classical corporate finance literature, insider equity ownership plays an important role in the motivation of efforts (e.g., Holmstrom 1982). Thus we use insider equity ownership as the proxy for the standard incentive scheme. Compact Disclosure database provides annual data of equity ownership of executive officers and directors for a large fraction of our IPO firms in our sample period.[12] Also, insiders generally still hold significant amount of their firms' equity at IPO and for a number of years after IPO. The average insider ownership in the first two years

[12] The insider equity ownership includes equity shares held by officers and directors, underlying shares in their vested stock options, and underlying shares in their stock options exercisable within 60 days of the reporting date. Annual compensation data for most of our IPO firms is not available. Thus this variable does not include the full incentive effect of stock options. However, we believe that the insider ownership data should capture the bulk part of total equity incentives provided to executive officers and directors.

after IPO in our sample is 25%. This implies that equity ownership should account for the bulk part of total equity incentives provided to executive officers and directors.

Model (1) of Table 10 shows that insider ownership is negatively related to the number of patents generated by a firm. The elasticity of patent counts to insider ownership is −0.073 and is statistically significant.[13] In model (2) we include the failure tolerance measure. Insider ownership still has a negative and significant association with innovation, while failure tolerance has a significantly positive effect as we have shown before. In models (3)–(4) we find similar opposite effects of insider ownership and failure tolerance on patent impact. While failure tolerance contributes to high-impact patents, insider equity ownership fails to do so.

In unreported regressions we examine whether the insider ownership effect on innovation is nonlinear. We use both a quadratic specification for insider ownership and a spline regression with ownership cutoffs being 5% and 25% (Morck, Shleifer, and Vishny 1988). We find that in no regions insider ownership is positively and significantly related to innovation.

Taken together, the findings in Table 10 are consistent with the implications in existing economic theories that while tolerance for failure is critical in encouraging innovation, standard incentive scheme such as insider equity ownership may fail to spur innovation. Clearly, insider ownership is not as exogenous as the failure tolerance measure. Thus we do not claim any causal effect of insider ownership on a firm's innovation productivity.

### 6.2 Failure Tolerance and Firm Value

In Section 5 we show that failure tolerance spurs corporate innovation. Does failure tolerance increase firm value? If innovation productivity is priced by investors, then we expect failure tolerance to increase firm value. But if the firm's operation focuses on standard tasks such as production and marketing rather than innovation, then as argued in Hellmann and Thiele (2009), failure tolerance may decrease firm value by undermining incentives for standard tasks.

In Table 11 we examine the effect of failure tolerance on firm value measured by Tobin's Q. We measure *Q* at the first fiscal year end after IPO. To be consistent in our economic interpretation, we use the natural logarithm of Tobin's Q as the dependent variable. To see whether failure tolerance is more important for firms in more innovative industries, we calculate

[13] In an unreported regression we add a firm-fixed effect in model (1) of Table 10. We find that Ln(Insider Ownership) is still negatively and significantly related to Ln(Patents). The coefficient estimate of insider ownership is -0.038 (p-value=0.012).

two industry level measures. "*Ind. Total Patents*" is the total number of patents in the entire sample period by 4-digit SIC industries. "*Ind. Total Citations*" is the total number of citations in the entire sample period by 4-digit SIC industries. A higher value of *Ind. Total Patents* or *Ind. Total Citations* indicates a more innovative industry.

Model (1) of Table 11 shows that after controlling for other firm characteristics, IPO firms backed by more failure-tolerant VCs have weakly higher firm values. The elasticity of firm value to failure tolerance is 0.081 and is marginally significant.

Next, we allow the effect of failure tolerance on firm value to vary with the importance of innovation in an industry. We expect investors to value failure tolerance more in industries in which innovation is more pertinent. Thus in model (2) we include the interaction between failure tolerance and *Ln(Ind. Total Patents)*. The direct effect of failure tolerance becomes negative and insignificant (–0.077). But the interaction effect is positive and significant (0.027). This implies that failure tolerance does not increase firm value in less innovative industries, and the effect of failure tolerance on firm value increases with the innovativeness of an industry. In model (3) we find similar effects when using *Ind. Total Citations* to identify more innovative industries.

In addition, the direct effect of *Ln(Ind. total Patents)* and *Ln(Ind. Total Citations)* are significantly positive, implying that the firm value is on average higher in more innovative industries. This is consistent with the findings in the existing literature (e.g., Hall 2000).

Overall, the analysis suggests that failure tolerance increases firm value in industries where innovation is more important.

## 7. CONCLUSION

The economic theories imply that motivating innovation is very different from motivating efforts in standard tasks. Tolerance for failure is crucial for a firm's innovation productivity. In this paper, we adopt a novel empirical approach to test these implications. 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 backed 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 with high ex-ante potentials but also high failure risk. VCs' tolerance for failure allows the startups' innovation potentials to be realized.

We also find that the failure tolerance effect on innovation persists long after VC investors exit the IPO firms. The effect is even more persistent if the VCs start to interact with the entrepreneurial firms in the firms' early development stages. Such persistence suggests that VC investors' attitudes toward failure have likely been internalized by the startup firms and become part of the firms' culture.

Overall, our findings support implications in recent theories on corporate innovation that failure tolerance is critical in motivating innovation. Our work also contributes to the literature on corporate culture by showing that a firm's first-generation insiders' attitudes about failure can have a significant and long-lasting impact on the firm's innovation productivity. Lastly, this study contributes to the VC literature showing that VC investors' tolerance for failure can contribute to the long-term comparative advantage and value of VC-backed startup firms.

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## Appendix A: Details in Variable Construction

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 tan 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 |
| 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* |
| Past IPO Exit$_{it}$ | The proportion of entrepreneurial firms financed by VC firm *i* that went public 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 1$^{st}$ round VC financing |
| # of VCs at 1$^{st}$-Round$_{i}$ | The number of investing VCs at the venture’s first-round investment |
| 1$^{st}$-Round Evaluation Interval$_{i}$ | Time interval in years between the 1st-round financing data and the 2nd-round financing date |
| **Innovation Variables (data source: NBER Patent Data)** | |
| Patent$_{it}$ | 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)** | |
| 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 |
| Sales $_{it}$ | Sales by firm *i* in year *t* (in $million) |
| Assets $_{it}$ | Total assets of 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 |
| 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* |
| Institutional Ownership $_{it}$ | Total percentage of firm *i*’s equity held by institutional investors in year *t* (Source: Thomson Financial 13f institutional holdings database) |
| Insider Ownership$_{it}$ | Total percentage of firm *i*’s equity held by officers and board of directors in year *t* (Source: Compact Disclosure) |
| 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 for the VC Sample**

This table reports the summary statistics for variables constructed based on our venture capital sample. The VC sample contains VC investments made by 2,857 VC firms from 1980 to 2006. All the variables listed below are time varying characteristics of a VC firm.

| Variable | 25% | Median | Mean | 75% | Std. Dev. | N |
|---|---|---|---|---|---|---|
| Failure Tolerance | 0.72 | 1.23 | 1.41 | 1.89 | 0.97 | 18,993 |
| Failure Tolerance 2 | 1.40 | 1.97 | 2.28 | 2.87 | 1.20 | 18,993 |
| *Other VC Characteristics* | | | | | | |
| Past Amount Invested (mil.) | 11.25 | 58.40 | 394.89 | 263.15 | 1298.07 | 35,662 |
| Past Firms Invested | 3.00 | 8.00 | 23.98 | 23.00 | 50.14 | 35,662 |
| Past Fund Raised (mil.) | 27.00 | 81.20 | 234.39 | 219.40 | 558.41 | 16,128 |
| VC Age | 3.00 | 6.00 | 8.64 | 12.00 | 8.06 | 28,260 |
| Investment Concentration | 0.08 | 0.28 | 0.37 | 0.72 | 0.33 | 34,270 |
| Past Successful Exit (%) | 25.00 | 60.00 | 52.82 | 77.76 | 34.41 | 35,689 |
| Past IPO Exit (%) | 0 | 8.33 | 16.18 | 24.05 | 22.74 | 35,689 |

**Table 2: Failure Tolerance and VC Experience**

The dependent variable is 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. Coefficient estimates and the Huber-White-Sandwich robust standard errors clustered by VC firm (in parentheses) are reported. ***, ** and * indicate significance at 1%, 5% and 10% levels respectively.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Ln(Past Amount Invested) | 0.034*** | | | |
| | (0.007) | | | |
| Ln(Past Firms Invested) | | 0.025** | | |
| | | (0.012) | | |
| Ln(Past Fund Raised) | | | 0.020*** | |
| | | | (0.004) | |
| Ln(VC Age) | | | | 0.055*** |
| | | | | (0.011) |
| Investment Concentration | 0.030*** | 0.023*** | 0.021*** | 0.008 |
| | (0.008) | (0.008) | (0.008) | (0.008) |
| Past Successful Exit (%) | -0.009 | 0.002 | 0.005 | 0.009 |
| | (0.011) | (0.011) | (0.011) | (0.011) |
| Constant | 0.675*** | 0.691*** | 0.712*** | 0.612*** |
| | (0.071) | (0.071) | (0.071) | (0.076) |
| 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 | 18,989 | 18,989 | 18,989 | 18,461 |
| $R^2$ | 0.142 | 0.135 | 0.141 | 0.171 |

**Table 3: Summary Statistics for the IPO Sample**

**Panel A: Failure Tolerance, VC Characteristics, and Project Characteristics**

| Variable | 25% | Median | Mean | 75% | Std. Dev. | N |
|---|---|---|---|---|---|---|
| Failure Tolerance | 1.32 | 1.76 | 1.80 | 2.26 | 0.69 | 1,848 |
| Failure Tolerance 2 | 2.20 | 2.84 | 2.92 | 3.54 | 1.02 | 1,848 |
| Past Amount invested (mil.) | 123.92 | 402.93 | 819.71 | 882.87 | 1595.73 | 1,848 |
| Past Firms invested | 17.62 | 37.65 | 56.60 | 70.97 | 64.18 | 1,848 |
| Past Fund Raised (mil.) | 53.77 | 167.95 | 425.65 | 398.64 | 1047.76 | 1,848 |
| VC Age | 8.18 | 12.33 | 13.28 | 17.18 | 6.84 | 1,848 |
| Investment Concentration | 0.04 | 0.10 | 0.14 | 0.17 | 0.15 | 1,848 |
| Past Successful Exit (%) | 63.26 | 70.24 | 64.71 | 75.55 | 21.33 | 1,848 |
| Past IPO Exit (%) | 17.85 | 23.81 | 24.38 | 30.16 | 13.06 | 1,848 |
| Early Stage | 0 | 1 | 0.63 | 1 | 0.48 | 1,848 |
| # of VCs at $1^{st}$-Round | 1 | 2 | 3.02 | 4 | 2.23 | 1,793 |
| $1^{st}$-Round Evaluation Interval | 0.59 | 1.01 | 1.63 | 1.84 | 1.98 | 1,726 |

**Panel B: Industry Distribution of IPO Firms**

This table reports the industry distributions for IPO firms separately for VC investors with *Failure Tolerance* above/below the IPO sample median. The industry classifications are based on the ones provided by the Venture Economics. Each number in the $2^{nd}$ and the $3^{rd}$ columns means the fraction of all projects from a given industry. Wilcoson Z-statistics is reported for the difference between each relevant pair of subsamples. *** indicates significance at 1% level.

| | *Failure Tolerance* above Median | *Failure Tolerance* below Median | Wilcoxon Z-statistics |
|---|---|---|---|
| Biotechnology | 0.137 | 0.099 | 2.472 |
| Medical/Health | 0.185 | 0.127 | 3.733*** |
| Computer Hardware | 0.058 | 0.070 | -1.029 |
| Computer Software | 0.179 | 0.149 | 1.680 |
| Computer Other | 0.002 | 0.002 | 0.008 |
| Semi-conducts/Other Elect | 0.080 | 0.086 | -0.487 |
| Internet Specific | 0.128 | 0.139 | -0.702 |
| Communications | 0.111 | 0.134 | -1.458 |
| Consumer Related | 0.075 | 0.052 | 2.014 |
| Business Services | 0.009 | 0.014 | -0.918 |
| Industrial/Energy | 0.037 | 0.057 | -1.972 |
| Manufacturing | 0.006 | 0.008 | -0.593 |
| Construction | 0.001 | 0.000 | 0.096 |
| Transportation | 0.005 | 0.012 | -1.625 |
| Agriculture/Forester/Fish | 0.000 | 0.002 | -1.420 |
| Other | 0.012 | 0.032 | -2.977*** |

**Panel C: 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 D: Control Variables**

| Variable | Mean | Median | Std. Dev. | N |
|---|---|---|---|---|
| Tobin's Q | 3.01 | 2.08 | 2.94 | 14,230 |
| Sales (mil.) | 375.07 | 51.77 | 2122.73 | 16,653 |
| Assets (mil.) | 485.46 | 76.78 | 2583.134 | 16,715 |
| 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 |
| Firm Age | 2.91 | 2.00 | 5.11 | 19,437 |
| PPE/Assets (%) | 17.36 | 11.19 | 17.46 | 16,670 |
| Institutional Ownership (%) | 37.58 | 32.31 | 29.01 | 13,061 |
| Insider Ownership (%) | 19.07 | 12.30 | 20.52 | 10,420 |
| Herfindahl Index | 0.24 | 0.11 | 0.31 | 19,437 |

**Table 4: 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). "Patents>0" refers to the subsample of firms with at least one patent during our sample period. Coefficient estimates and the Huber-White-Sandwich robust standard errors clustered by IPO firm (in parentheses) are reported. ***, ** and * indicate significance at 1%, 5% and 10% levels respectively.

| | Ln(Patents) | | Ln(Citations/Patent) | |
|---|---|---|---|---|
| | Full Sample | Patents>0 | Full Sample | Patents>0 |
| | (1) | (2) | (3) | (4) |
| Ln(Failure Tolerance) | 0.258** | 0.422*** | 0.201** | 0.310** |
| | (0.113) | (0.159) | (0.093) | (0.122) |
| Ln(Sales) | 0.097*** | 0.117*** | 0.030** | 0.032** |
| | (0.019) | (0.022) | (0.014) | (0.015) |
| ROA | 0.677*** | 0.564*** | 0.388*** | -0.014 |
| | (0.141) | (0.197) | (0.125) | (0.174) |
| R&D/Assets | 1.520*** | 1.052*** | 1.066*** | 0.223 |
| | (0.286) | (0.356) | (0.248) | (0.310) |
| CapExp/Assets | 2.017*** | 3.071*** | 1.259** | 1.968** |
| | (0.586) | (0.919) | (0.584) | (0.880) |
| Leverage | -0.813*** | -0.689*** | -0.755*** | -0.691*** |
| | (0.162) | (0.237) | (0.133) | (0.195) |
| Tobin's Q | 0.093*** | 0.072*** | 0.071*** | 0.040*** |
| | (0.015) | (0.017) | (0.012) | (0.014) |
| Institutional Ownership | 1.006*** | 1.436*** | 0.812*** | 1.142*** |
| | (0.188) | (0.257) | (0.145) | (0.188) |
| Firm Age | 0.058*** | 0.035 | 0.016 | -0.013 |
| | (0.018) | (0.024) | (0.010) | (0.013) |
| PPE/Assets | 0.124 | 0.255 | -0.078 | -0.198 |
| | (0.361) | (0.563) | (0.317) | (0.461) |
| Herfindahl Index | -0.252 | -0.144 | -0.095 | 0.144 |
| | (0.181) | (0.279) | (0.158) | (0.225) |
| Constant | 0.149 | 0.496 | -3.139** | -4.235*** |
| | (0.607) | (0.836) | (1.386) | (0.508) |
| Industry fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Observations | 11,994 | 7,607 | 11,994 | 7,607 |
| $R^2$ | 0.315 | 0.257 | 0.253 | 0.261 |

## Table 5: Controlling for VC Experience and Project Selection Ability

In this table we control for VC firm experience and lead VC firm fixed effects. The controls variables are the same as in Table 4. Coefficient estimates and the Huber-White-Sandwich robust standard errors clustered by IPO firm (in parentheses) are reported. ***, ** and * indicate significance at 1%, 5% and 10% levels respectively.

### Panel A: Controlling for VC Experience and Lead VC Fixed-Effects

| **Dependent Variable: Ln(Patents)** | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Ln(Failure Tolerance) | 0.230* | 0.253** | 0.252** | 0.343*** |
| | (0.125) | (0.125) | (0.125) | (0.128) |
| Investment Concentration | 0.210 | 0.019 | 0.189 | 0.233 |
| | (0.432) | (0.446) | (0.398) | (0.390) |
| Past Successful Exit | 0.482 | 0.709* | 0.565* | 0.367 |
| | (0.431) | (0.417) | (0.309) | (0.249) |
| Ln(Past Amount Invested) | -0.014 | | | |
| | (0.050) | | | |
| Ln(Past Firms Invested) | | -0.076 | | |
| | | (0.075) | | |
| Ln(Past Fund Raised) | | | -0.035 | |
| | | | (0.039) | |
| Ln(VC Age) | | | | -0.144 |
| | | | | (0.126) |
| Controls, industry, and year fixed effects | Yes | Yes | Yes | Yes |
| Lead VC fixed effects | Yes | Yes | Yes | Yes |
| Observations | 11,994 | 11,994 | 11,994 | 11,911 |
| $R^2$ | 0.354 | 0.354 | 0.354 | 0.356 |

| **Dependent Variable: Ln(Citations/Patent)** | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Ln(Failure Tolerance) | 0.188* | 0.207* | 0.219** | 0.302*** |
| | (0.109) | (0.109) | (0.109) | (0.112) |
| Investment Concentration | 0.180 | 0.010 | 0.159 | 0.238 |
| | (0.348) | (0.360) | (0.323) | (0.316) |
| Past Successful Exit | 0.371 | 0.554* | 0.476* | 0.201 |
| | (0.332) | (0.315) | (0.252) | (0.219) |
| Ln(Past Amount Invested) | -0.023 | | | |
| | (0.038) | | | |
| Ln(Past Firms Invested) | | -0.081 | | |
| | | (0.057) | | |
| Ln(Past Fund Raised) | | | -0.053* | |
| | | | (0.032) | |
| Ln(VC Age) | | | | -0.155 |
| | | | | (0.099) |
| Controls, industry, and year fixed effects | Yes | Yes | Yes | Yes |
| Lead VC fixed effects | Yes | Yes | Yes | Yes |
| Observations | 11,994 | 11,994 | 11,994 | 11,911 |
| $R^2$ | 0.274 | 0.274 | 0.274 | 0.275 |

**Panel B: Failure Tolerance and Project Selection Ability**

"Selection Ability" is the principal-component factor of the six VC characteristics: Investment Concentration, Past Successful Exit, Ln(Past Amount Invested), Ln(Past Firms Invested), Ln(Past Fund Raised), and Ln(VC Age). The variable is scaled so that it is between zero and one, with a higher value meaning a higher selection ability.

| | (1)<br>Ln(Patents) | (2)<br>Ln(Citations/Patent) |
|---|---|---|
| Ln(Failure Tolerance) | 0.578** | 0.568** |
| | (0.270) | (0.250) |
| Ln(Failure Tolerance) × Selection Ability | -0.648 | -0.697 |
| | (0.491) | (0.439) |
| Selection Ability | 0.574* | 0.405 |
| | (0.338) | (0.296) |
| Constant | -2.493* | -2.375** |
| | (1.318) | (1.099) |
| Controls | Yes | Yes |
| Industry, and year fixed effects | Yes | Yes |
| Lead VC fixed effects | Yes | Yes |
| Observations | 11,911 | 11,911 |
| $R^2$ | 0.355 | 0.275 |

## Table 6: Controlling for Selection by Industry

### Panel A: Regression Analysis

This panel reports univariate comparison of failure tolerance across different patent categories. *** indicates significance at 1% level.

| Failure Tolerance | Drugs & Chemical (1) | Computers & Electrical (2) | Software (3) | Miscellaneous (4) |
|---|---|---|---|---|
| Median (Mean) | 1.85 (1.88) | 1.69 (1.75) | 1.77 (1.84) | 1.55 (1.64) |
| Standard Deviation | 0.60 | 0.66 | 0.74 | 0.73 |
| Wilcoxon Z relative to category (1) | | -11.60*** | -5.08*** | -11.77*** |

### Panel B: Cross Patent Category Comparison of Failure Tolerance Effect

The patent categories are based on the classifications in Hall, Jaffe, and Trajtemberg (2005). The controls are the same as in Table 4. The bottom row of each table reports the results from the Chi-square test of the difference in the failure tolerance effect between category (1) and another patent category. Coefficient estimates and the Huber-White-Sandwich robust standard errors clustered by IPO firm (in parentheses) are reported. ***, ** and * indicate significance at 1%, 5% and 10% levels respectively.

| Dependent Variable: Ln(Patents) | Drugs & Chemical (1) | Computers & Electrical (2) | Software (3) | Miscellaneous (4) |
|---|---|---|---|---|
| Ln(Failure Tolerance) | 0.743** | 0.255** | 0.190** | 0.313*** |
| | (0.306) | (0.102) | (0.076) | (0.091) |
| Controls and Constant | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Observations | 3,177 | 3,580 | 2,911 | 2,277 |
| $R^2$ | 0.207 | 0.243 | 0.155 | 0.296 |
| Comparison of Failure Tolerance effect with (1) (p-value) | | -0.488*** | -0.553*** | -0.430*** |
| | | (0.004) | (<0.001) | (0.004) |

| Dependent Variable: Ln(Citations/Patent) | Drugs & Chemical (1) | Computers & Electrical (2) | Software (3) | Miscellaneous (4) |
|---|---|---|---|---|
| Ln(Failure Tolerance) | 0.576** | 0.199** | 0.177** | 0.185** |
| | (0.225) | (0.101) | (0.088) | (0.089) |
| Controls and Constant | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Observations | 3,177 | 3,580 | 2,911 | 2,277 |
| $R^2$ | 0.249 | 0.189 | 0.132 | 0.262 |
| Comparison of Failure Tolerance effect with (1) (p-value) | | -0.377** | -0.399*** | -0.391*** |
| | | (0.017) | (0.008) | (0.010) |

## Table 7: Controlling for Ex-Ante Project Characteristics

### Panel A: Failure Tolerance and Ex-Ante Project Characteristics

This panel reports the median (mean) VC failure tolerance in subsamples based on low/high values of each ex-ante project characteristic. Wilcoxon Z-statistics is reported for the difference between each relevant pair of subsamples.

| Failure Tolerance | Early Stage | | # of VCs at 1st-Round | | 1st-Round Evaluation Interval | |
|---|---|---|---|---|---|---|
| | = 0 | = 1 | ≤ median | > median | ≤ median | > median |
| Median (Mean) | 1.69 (1.77) | 1.79 (1.81) | 1.74 (1.78) | 1.79 (1.81) | 1.77 (1.81) | 1.75 (1.78) |
| Wilcoxon Z | -2.14** | | -1.40 | | 1.32 | |

### Panel B: Regression Analysis

In this panel we control for ex-ante project characteristics as well as VC firm characteristics. The controls variables are the same as in Table 4. Coefficient estimates and the Huber-White-Sandwich robust standard errors clustered by IPO firm (in parentheses) are reported. ***, ** and * indicate significance at 1%, 5% and 10% levels respectively.

| Dependent Variable Ln(Patents) | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Ln(Failure Tolerance) | 0.250* | 0.272** | 0.270** | 0.350*** |
| | (0.135) | (0.135) | (0.135) | (0.134) |
| Early Stage | 0.236** | 0.231** | 0.233** | 0.222* |
| | (0.116) | (0.116) | (0.117) | (0.116) |
| # of VCs at 1st-Round | 0.028 | 0.027 | 0.027 | 0.028 |
| | (0.024) | (0.024) | (0.025) | (0.024) |
| Ln(1st-Round Evaluation Interval) | -0.103* | -0.101* | -0.103* | -0.102* |
| | (0.060) | (0.060) | (0.060) | (0.060) |
| Investment Concentration | 0.201 | 0.026 | 0.164 | 0.193 |
| | (0.477) | (0.492) | (0.430) | (0.422) |
| Past Successful Exit | 0.334 | 0.550 | 0.442 | 0.345 |
| | (0.461) | (0.445) | (0.336) | (0.268) |
| Ln(Past Amount Invested) | -0.004 | | | |
| | (0.053) | | | |
| Ln(Past Firms Invested) | | -0.059 | | |
| | | (0.079) | | |
| Ln(Past Fund Raised) | | | -0.027 | |
| | | | (0.041) | |
| Ln(VC Age) | | | | -0.127 |
| | | | | (0.131) |
| Controls, industry, and year fixed effects | Yes | Yes | Yes | Yes |
| Lead VC fixed effects | Yes | Yes | Yes | Yes |
| Observations | 11,212 | 11,212 | 11,212 | 11,158 |
| $R^2$ | 0.354 | 0.354 | 0.354 | 0.356 |

**(Table 7 continued)**

**Panel B continued**

| **Dependent Variable Ln(Citations/Patent)** | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Ln(Failure Tolerance) | 0.205* | 0.223* | 0.236** | 0.306*** |
| | (0.118) | (0.118) | (0.117) | (0.118) |
| Early Stage | 0.288*** | 0.285*** | 0.285*** | 0.279*** |
| | (0.098) | (0.097) | (0.097) | (0.097) |
| # of VCs at 1st-Round | 0.050** | 0.049** | 0.048** | 0.050** |
| | (0.021) | (0.021) | (0.022) | (0.021) |
| Ln(1st-Round Evaluation Interval) | -0.065 | -0.063 | -0.065 | -0.065 |
| | (0.045) | (0.045) | (0.045) | (0.045) |
| Investment Concentration | 0.145 | -0.008 | 0.112 | 0.179 |
| | (0.390) | (0.402) | (0.354) | (0.348) |
| Past Successful Exit | 0.260 | 0.430 | 0.396 | 0.207 |
| | (0.358) | (0.342) | (0.276) | (0.233) |
| Ln(Past Amount Invested) | -0.015 | | | |
| | (0.042) | | | |
| Ln(Past Firms Invested) | | -0.066 | | |
| | | (0.062) | | |
| Ln(Past Fund Raised) | | | -0.048 | |
| | | | (0.034) | |
| Ln(VC Age) | | | | -0.145 |
| | | | | (0.103) |
| Controls, industry, and year fixed effects | Yes | Yes | Yes | Yes |
| Lead VC fixed effects | Yes | Yes | Yes | Yes |
| Observations | 11,212 | 11,212 | 11,212 | 11,158 |
| $R^2$ | 0.279 | 0.279 | 0.279 | 0.280 |

**Table 8: 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. Coefficient estimates and the Huber-White-Sandwich robust standard errors clustered by IPO firm (in parentheses) are reported. ***, ** and * indicate significance at 1%, 5% and 10% levels respectively.

| | Ln(Patents) | | Ln(Citations/Patent) | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Ln(Failure Tolerance) | 0.034 | 0.063 | -0.040 | -0.004 |
| | (0.157) | (0.155) | (0.118) | (0.126) |
| Ln(Failure Tolerance) × Early Stage | 0.422** | 0.404** | 0.456*** | 0.422** |
| | (0.213) | (0.205) | (0.176) | (0.173) |
| Early Stage | 0.184 | 0.090 | 0.158 | 0.145 |
| | (0.143) | (0.141) | (0.123) | (0.123) |
| Ln(Sales) | 0.097*** | 0.080*** | 0.030** | 0.022 |
| | (0.019) | (0.017) | (0.013) | (0.014) |
| ROA | 0.720*** | 0.745*** | 0.429*** | 0.441*** |
| | (0.139) | (0.138) | (0.123) | (0.126) |
| R&D/Assets | 1.486*** | 1.422*** | 1.031*** | 0.955*** |
| | (0.282) | (0.268) | (0.244) | (0.241) |
| CapExp/Assets | 2.026*** | 1.510*** | 1.269** | 0.819 |
| | (0.586) | (0.547) | (0.585) | (0.572) |
| Leverage | -0.790*** | -0.731*** | -0.733*** | -0.680*** |
| | (0.163) | (0.146) | (0.131) | (0.128) |
| Tobin's Q | 0.091*** | 0.079*** | 0.069*** | 0.063*** |
| | (0.015) | (0.012) | (0.012) | (0.012) |
| Institutional Ownership | 0.966*** | 0.985*** | 0.774*** | 0.746*** |
| | (0.188) | (0.166) | (0.145) | (0.142) |
| Firm Age | 0.060*** | 0.052*** | 0.018* | 0.011 |
| | (0.018) | (0.016) | (0.010) | (0.011) |
| PPE/Assets | 0.109 | 0.397 | -0.093 | 0.154 |
| | (0.362) | (0.354) | (0.320) | (0.320) |
| Herfindahl Index | -0.253 | -0.265 | -0.096 | -0.053 |
| | (0.182) | (0.177) | (0.159) | (0.163) |
| Constant | -3.798** | -3.820** | -3.242** | -3.624*** |
| | (1.546) | (1.605) | (1.278) | (1.375) |
| Observable VC Characteristics | | Yes | | Yes |
| Lead VC fixed effects | | Yes | | Yes |
| Industry fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Observations | 11,994 | 11,994 | 11,994 | 11,994 |
| $R^2$ | 0.320 | 0.357 | 0.258 | 0.278 |

**Table 9: Persistence of the Failure Tolerance Effect**

All regressions are restricted to the sub-sample firms that have existed for at least eight years after the IPO year (i.e., Firm Age ≥ 8). We regress innovation on failure tolerance and control variables separately for each year. Then we take the average of the coefficient estimate for Ln(Failure Tolerance) in each age group. We also report the number of significant estimates and the average number of observations in a regression in each age group. "Early-Stage Ventures" includes IPO firms in this sub-sample that received first-round VC financing when they were in the "Startup/Seed" stage or the "Early Stage".

**Panel A:Ln(Patents)**

| **Entire Sub-Sample** | (1)<br>1 ≤ Firm Age < 3 | (2)<br>3 ≤ Firm Age < 6 | (3)<br>6 ≤ Firm Age ≤ 8 |
|---|---|---|---|
| Average estimate: Ln(Failure Tolerance) | 0.451 | 0.473 | 0.327 |
| Number of significant estimates | 2 out of 2 | 3 out of 3 | 0 out of 3 |
| Average observations per year | 600 | 640 | 640 |

| **Early-Stage Ventures in Sub-Sample** | (1)<br>1 ≤ Firm Age < 3 | (2)<br>3 ≤ Firm Age < 6 | (3)<br>6 ≤ Firm Age ≤ 8 |
|---|---|---|---|
| Average estimate: Ln(Failure Tolerance) | 0.672 | 0.859 | 0.719 |
| Number of significant estimates | 2 out of 2 | 3 out of 3 | 3 out of 3 |
| Average observations per year | 376 | 400 | 400 |

**Panel B: Ln(Citations/Patent)**

| **Entire Sub-Sample** | (1)<br>1 ≤ Firm Age < 3 | (2)<br>3 ≤ Firm Age < 6 | (3)<br>6 ≤ Firm Age ≤ 8 |
|---|---|---|---|
| Average estimate: Ln(Failure Tolerance) | 0.450 | 0.232 | 0.108 |
| Number of significant estimates | 1 out of 2 | 0 out of 3 | 0 out of 3 |
| Average observations per year | 600 | 640 | 640 |

| **Early-Stage Ventures in Sub-Sample** | (1)<br>1 ≤ Firm Age < 3 | (2)<br>3 ≤ Firm Age < 6 | (3)<br>6 ≤ Firm Age ≤ 8 |
|---|---|---|---|
| Average estimate: Ln(Failure Tolerance) | 0.744 | 0.705 | 0.312 |
| Number of significant estimates | 2 out of 2 | 3 out of 3 | 1 out of 3 |
| Average observations per year | 376 | 400 | 400 |

**Table 10: Insider Ownership, Failure Tolerance and Corporate Innovation**

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

| | Ln(Patents) | | Ln(Citations/Patent) | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Ln(Insider ownership) | -0.073*** | -0.062*** | -0.062*** | -0.052** |
| | (0.021) | (0.022) | (0.019) | (0.020) |
| Ln(Failure Tolerance) | | 0.264** | | 0.194* |
| | | (0.125) | | (0.108) |
| Ln(Sales) | 0.105*** | 0.102*** | 0.030* | 0.030* |
| | (0.021) | (0.021) | (0.017) | (0.016) |
| ROA | 0.668*** | 0.702*** | 0.387*** | 0.396*** |
| | (0.162) | (0.166) | (0.146) | (0.149) |
| R&D/Assets | 1.653*** | 1.513*** | 1.265*** | 1.168*** |
| | (0.337) | (0.344) | (0.299) | (0.304) |
| CapExp/Assets | 2.170*** | 2.082*** | 1.131* | 1.080 |
| | (0.677) | (0.669) | (0.681) | (0.683) |
| Leverage | -0.925*** | -0.902*** | -0.889*** | -0.876*** |
| | (0.186) | (0.190) | (0.160) | (0.163) |
| Tobin's Q | 0.100*** | 0.100*** | 0.084*** | 0.083*** |
| | (0.016) | (0.016) | (0.014) | (0.014) |
| Institutional Ownership | 1.128*** | 1.048*** | 0.974*** | 0.919*** |
| | (0.208) | (0.212) | (0.172) | (0.175) |
| Firm Age | 0.055** | 0.065*** | 0.005 | 0.011 |
| | (0.022) | (0.023) | (0.015) | (0.015) |
| PPE/Assets | -0.187 | 0.171 | -0.087 | 0.122 |
| | (0.408) | (0.405) | (0.364) | (0.370) |
| Herfindahl Index | -0.530*** | -0.344* | -0.311* | -0.156 |
| | (0.196) | (0.207) | (0.178) | (0.191) |
| Constant | -2.272 | -3.241* | -2.122 | -3.010** |
| | (1.955) | (1.718) | (1.740) | (1.433) |
| Industry fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Observations | 9,934 | 9,452 | 9,934 | 9,452 |
| $R^2$ | 0.314 | 0.322 | 0.236 | 0.241 |

**Table 11: Failure Tolerance and Firm Value**

The dependent variable is the natural logarithm of a firm's Tobin's Q at the first fiscal year end after IPO. "Ind. Total Patents" and "Ind. Total Citations" are the total number of patents and the total number of citations in the entire sample period by 4-digit SIC industries, respectively. Coefficient estimates and the Huber-White-Sandwich robust standard errors (in parentheses) are reported. ***, ** and * indicate significance at 1%, 5% and 10% levels respectively.

| | (1) | (2) | (3) |
|---|---|---|---|
| Ln(Failure Tolerance) | 0.081* | -0.077 | -0.124 |
| | (0.046) | (0.082) | (0.086) |
| Ln(Failure Tolerance) x Ln(Ind. Total Patents) | | 0.027** | |
| | | (0.013) | |
| Ln(Ind. Total Patents) | | 0.044*** | |
| | | (0.013) | |
| Ln(Failure Tolerance) x Ln(Ind. Total Citations) | | | 0.032** |
| | | | (0.014) |
| Ln(Ind. Total Citations) | | | 0.043*** |
| | | | (0.014) |
| Ln(Insider Ownership) | 0.029*** | 0.029*** | 0.029*** |
| | (0.011) | (0.011) | (0.011) |
| Ln(Sales) | -0.013* | -0.014* | -0.013* |
| | (0.007) | (0.007) | (0.007) |
| ROA | 0.206* | 0.166 | 0.175* |
| | (0.106) | (0.104) | (0.105) |
| R&D/Assets | 1.040*** | 0.822*** | 0.863*** |
| | (0.210) | (0.209) | (0.209) |
| CapExp/Assets | 1.063*** | 1.196*** | 1.168*** |
| | (0.328) | (0.327) | (0.323) |
| Leverage | 0.255*** | 0.287*** | 0.283*** |
| | (0.086) | (0.085) | (0.085) |
| Institutional Ownership | -0.106 | -0.076 | -0.056 |
| | (0.118) | (0.117) | (0.118) |
| PPE/Assets | -0.887*** | -0.909*** | -0.860*** |
| | (0.168) | (0.164) | (0.163) |
| Herfindahl Index | -0.091 | 0.090 | 0.089 |
| | (0.077) | (0.081) | (0.081) |
| Constant | 0.804*** | 0.393 | 0.500* |
| | (0.308) | (0.305) | (0.294) |
| Industry fixed effects | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes |
| Observations | 1,367 | 1,367 | 1,367 |
| $R^2$ | 0.277 | 0.294 | 0.292 |