Propagation of Financial Shocks: The Case of Venture Capital*

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Abstract

This paper investigates how venture-backed companies are affected when others sharing the same investor perform poorly. I show that in theory companies may be helped or hurt. Empirically, I estimate the impact of the technology bubble's collapse on non-information-technology companies held alongside internet companies in venture portfolios. I find the collapse was associated with a 26% larger decline in the probability of raising additional financing for these non-IT companies compared with others. I control for unobservable characteristics by examining companies with multiple investors. The results suggest that the seemingly robust structure of venture intermediaries does not eliminate/reverse contagion among portfolio companies.

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1 Introduction

The structure of venture capital investment firms (henceforth "venture firms" or "venture investors") differs from that of other intermediaries in several ways that ostensibly make them less fragile and more self-contained. First, investors in a venture fund are required to commit capital for the entire life of the fund (typically 10 years), thus there are no issues of maturity mismatch in assets and liabilities. Second, venture firms are often limited in the extent to which they can invest in the same company out of multiple funds under their management. In this paper, I examine the impact of this unique intermediation structure on portfolio companies. In particular, I examine how companies' access to capital is affected when the prospects of others held in the same portfolio decline.

I demonstrate in a simple model that it is ambiguous whether companies would be helped or hurt in this scenario, given the institutional features just described. On the one hand, after a negative shock to some companies in a venture portfolio, unrelated companies would become more attractive in relative terms. All else equal, this would make it easier for them to obtain continuation financing. This relates closely to the "bright side" view of internal capital markets, in which corporate headquarters engages in relative evaluation (Stein, 1997). On the other hand, a venture investment firm with high exposure to the shock may experience more difficulty raising new funds from limited partners. I show that if venture firm fundraising is sufficiently sensitive to interim performance, this can make it more difficult for portfolio companies unrelated to the shock to obtain continuation financing. This turns out to be true even if there are cross-fund investing restrictions prohibiting new funds from being invested in existing portfolio companies. Thus, the direction of contagion (reverse contagion vs. ordinary contagion) among venture-backed portfolio companies is ultimately an empirical question. Knowing the answer to this would improve not only our understanding of venture capital, but of financial intermediation more broadly. In particular, if ordinary contagion occurs even in the absence of maturity mismatch, this may be informative when considering policies to reduce the fragility of other intermediaries.

In terms of the venture capital setting specifically, it is also true that contagion would likely be of particular consequence in this context. Indeed, for mature companies, disruptions in intermediary relationships may be harmful but survivable. By contrast, for typical venture-backed companies, with negative earnings and few tangible assets, these disruptions are much more likely to lead to company failure. Moreover, such failures are especially important given the nature of the companies financed by venture firms. Many of the largest companies in the U.S. by market capitalization, including Apple, Google, Microsoft, and Cisco, were backed by venture firms in their early days. In addition, more than 60% of the IPOs that have occurred since 1999 have been venture-backed (Kaplan and Lerner, 2010). Given that venture firms provide capital to highly innovative companies with the potential to create large social surpluses, distortions in their capital allocation decisions could have important welfare implications.

Finally, while data on venture-backed companies are known to be limited in many respects, they are actually particularly well-suited for examining these issues. In the venture capital setting, one can observe each venture firm's exposure to various sectors, each portfolio company's ability to raise continuation financing, as well as all links between portfolio companies and venture firms. This makes it possible to investigate whether companies have increased (decreased) difficulty raising follow-on rounds *from any venture firm* when they are held in the same portfolio as companies in a declining sector. Much of the work examining the impact of intermediary liquidity shocks has made use of data only from the intermediary side. With such data, it is possible to investigate whether intermediaries that suffer shocks cut back lending to unrelated clients. However, it is not possible to determine whether those clients are able to compensate by raising capital from others. This requires matched intermediary-client data of the kind used in this study. Such data have been difficult to obtain in other settings, particularly in nations with well-developed financial systems. The other advantage of using matched data is that this allows me to take advantage of the fact that portfolio companies can have multiple venture investors. It is then possible to include portfolio company fixed effects in some specifications to control for unobservable company characteristics.

The empirical strategy employed in this paper is to examine continuation financing outcomes for venture-backed companies in sectors unrelated to information technology (IT) during the period surrounding the collapse of the technology bubble in early 2000. In particular, I exploit variation in the degree of venture firms' exposure to the internet sector, which largely results from the fact that some firms specialize in non-IT investments while others diversify across sectors (Gompers, Kovner, and Lerner, 2009; Hochberg and Westerfield, 2011). The basic premise is that, if a non-IT company were held in the same portfolio as many internet companies, it may have faced greater (less) difficulty raising follow-on rounds after the technology bubble burst.

I use semi-parametric survival analysis to estimate the effect of various factors on the instantaneous probability, or "hazard," of raising a follow-on round. The most basic specification can be thought of as analogous to a difference-in-differences framework. In this case, a company is considered to be in the treatment group if its backers invested heavily in internet companies during the years leading up to the peak of the technology bubble. Similarly, a company is considered to be in the control group if its backers invested little in the internet sector during that time. I estimate that non-IT companies in the treatment group experienced a 26% larger decline in continuation hazard with the collapse of the bubble than did those in the control group.

The primary concern with this identification strategy is that companies backed by more internet-focused venture firms may have differed from others in ways that also made their prospects decline more when the bubble burst. I address this issue in several ways. First, as already mentioned, I limit the sample to only non-IT companies, as these were less likely to be related to internet technologies, regardless of investor internet exposure. However, while the prospects of, say, a biotech company might not directly relate to the internet, other stories are certainly plausible. For example, companies backed by more internet-focused investors may have been disproportionately located in Northern California and suffered due to a decline in the local economy. To account for the fact that some non-IT companies may have suffered more than others when the bubble burst, due to such observable characteristics, I include a large set of controls. Controlling for these factors does not substantially change the estimated effect of investor internet exposure. Finally, I exploit the fact that companies can have multiple venture investors. This allows me to include company fixed-effects to control for unobservable company characteristics, analogous to Khwaja and Mian (2008) and Schnabl (2010). I find that for the same portfolio company receiving capital from multiple venture firms, investors with greater internet exposure were significantly less likely to continue participating in follow-on rounds. This provides perhaps the clearest evidence that the baseline results are not driven by unobservable company characteristics such as IT-relatedness.

Next, I explore the mechanism underlying these results. As mentioned earlier, one reason that poor performance in one part of a venture firm's portfolio might negatively affect continuation financing decisions in another part is that poor performance may lead to increased difficulty in raising new funds from limited partners. I confirm that, for an average venture firm, a one standard deviation increase in internet exposure was associated with an additional 13% decrease in fundraising hazard when the bubble burst.

A venture firm that had not raised a new fund from limited partners recently would likely be more concerned about a decline in its fundraising capacity (due to internet exposure) than a firm that just raised a new fund. Likewise, a young firm with a short investment track record would likely be more concerned than a well-established firm. Thus, if venture firm fundraising were driving the baseline results, one would expect the negative effect of a venture firm's internet exposure on its portfolio companies to be strongest for young venture firms and firms that had not raised a new fund recently. I find that this was indeed the case.

Finally, I examine whether there is evidence to suggest that non-IT companies funded by more internet-focused venture firms during the bubble tended to be of lower quality. To shed light on this, I test whether the patenting productivity of companies whose investors had high internet exposure was lower prior to the collapse of the bubble. I find no evidence that these companies were less productive in terms of the number of patents they produced or the number of citations those patents received. It should also be noted that even if these companies did differ in terms of quality, this would not present an obvious endogeneity problem. Again, due to the difference-in-differences framework employed, the primary identification challenge comes from unobservable differences in the *change* in company prospects coinciding with the end of the bubble, not unobservable differences in the overall *level* of company prospects. Put differently, even if internet-focused venture firms invested in lower quality companies, those companies would have been of lower quality both before and after the bubble burst. This would not necessarily account for the greater decline they experienced in their probability of raising follow-on rounds.

This paper relates perhaps most closely to a line of research that studies the effect of a bank's health on the value of its borrowers. Several papers make use of the event study methodology to estimate abnormal returns for clients of troubled banks following announcements of distress/failure (Slovin, Sushka, and Polonchek, 1993; Yamori and Murakami, 1999; Bae, Kang, and Lim, 2002; Ongena, Smith, and Michalsen, 2003; Djankov, Jindra, and

Klapper, 2005). Others examine client returns during periods of more general bank distress, exploiting cross-sectional variation in companies' bank dependency (Kang and Stulz, 2000; Chava and Purnanandam, 2011) or banks' exposure to depressed assets (Gan, 2007). In general, these studies find that bank distress leads to a significant decline in client value, suggesting that relationships cannot be costlessly replaced.

A distinct but closely related line of research studies whether bank liquidity shocks affect loan supply. Shocks from changes in monetary policy (Bernanke and Blinder, 1992; Kashyap, Stein, and Wilcox, 1993; Kashyap and Stein, 2000; Kishan and Opiela, 2000) as well as other sources (Peek and Rosengren, 1995, 1997; Paravisini, 2008; Popov and Udell, 2010; Puri, Rocholl, and Steffen, 2010) have been shown to lead banks to decrease lending. Less clear, however, is the extent to which these fluctuations in loan supply are smoothed out by clients of affected banks. Recent evidence from matched intermediary-client data has suggested that borrowers are unable to smooth bank shocks completely in emerging markets (Khwaja and Mian, 2008; Schnabl, 2010).

This paper differs in its focus on venture capital. Unlike a bank, a venture firm with poor-performing investments would not have to shrink its balance sheet to meet capital adequacy requirements. Also, unlike a bank, a venture firm would not face runs from various types of short-term liability holders in response to (real or perceived) poor performance. Indeed, as described above, one might actually expect to find reverse contagion in the venture context. To the extent that ordinary contagion does occur, it is likely driven by future fundraising considerations, rather than runs by limited partners on existing funds. Fundraising considerations have been found to lead to distortions in venture financing, such as "grandstanding" (Gompers, 1996) and "money chasing deals" (Gompers and Lerner, 2000). This paper can be thought of as documenting another such distortion.

The rest of the paper proceeds as follows. Section 2 provides background on the basic features of the venture capital industry and provides a simple model of contagion in venture capital. Section 3 discusses the empirical strategy used. Section 4 discusses the data and construction of key variables. Section 5 presents the results. Section 6 concludes.

2 Venture Capital and Contagion

2.1 The Venture Capital Industry

The vast majority of venture capital funds are structured as limited partnerships. Investors in these funds are typically large institutions and wealthy individuals. These investors commit capital to a fund that can be invested during a predetermined period of time, usually 10 to 12 years. After this time, funds must be liquidated and final profits distributed. Venture funds are typically close-ended in the sense that once a fund is launched, it will not raise further commitments from investors. Therefore, in order for a venture firm to survive and continue making new investments, it must raise a new fund periodically, usually every three to five years. Due to potential conflicts of interest, partnership agreements typically limit the extent to which a venture firm can use a new fund to finance a portfolio company from a previous fund (Rossa and Tracy, 2007).[1] Despite these restrictions, however, a venture firm having trouble raising a new fund may still become more selective with its existing capital in order to "keep its powder dry" for new potential investments. Put differently, venture firms try to avoid having fully invested their previous fund without yet having raised their next fund, as the loss of deal flow is very costly, both in terms of missed opportunities and

[1] This restriction is intended to prevent a scenario where the general partner might find it optimal to invest in a struggling company from a previous fund with capital from a new fund with the hopes of salvaging the investment, or temporarily keeping the valuation high for window-dressing purposes. Consequently, partnership agreements for second or later funds frequently contain provisions that the fund's advisory board must review such investments or that a (super-)majority of limited partners approve these transactions. Another way in which these problems are limited is by the requirement that the earlier fund invest simultaneously at the same valuation. Alternatively, the investment may be allow only if one or more unaffiliated funds simultaneously invest at the same price (Lerner, Hardymon, and Leamon, 1994).

reputation.

There is considerable heterogeneity in the investment strategies employed by venture capital firms. Some firms specialize in making investments within a particular sector, while others diversify across several sectors. Domain Associates, for example, is a specialist firm that focuses on life sciences. Alta Partners, on the other hand, is a generalist firm with investments in both life sciences and information technology. Hochberg and Westerfield (2011) argue that fund size and specialization are substitutes in venture capital, and also that more skilled firms should tend to be less specialized. Consistent with their model, they find that larger and more experienced venture firms tend to invest more broadly. Indeed, many of the most well-established firms such as Kleiner Perkins are generalist investors. During the technology bubble, it was, of course, tempting for generalist firms to invest heavily in internet companies, as these companies were easy to take public.

The structure of financing for venture-backed portfolio companies parallels that of their financiers. Just as venture capital firms must periodically raise new funds from limited partners, venture-backed portfolio companies must periodically raise new rounds of financing from their venture capitalists. Many have interpreted staged financing as a way of mitigating agency problems (Gompers, 1995; Kaplan and Strömberg, 2003).

2.2 A Simple Model of Contagion in Venture Capital

Given the structure of venture capital financing just described, the potential mechanisms by which shocks might propagate across companies in a venture firm's portfolio would have to be quite different from those at work in other contexts. Below I provide a simple model to illustrate that, unlike in most other settings, contagion could go in either direction in venture capital.

2.2.1 A Single-Fund Venture Firm

I begin by considering a venture firm that raises a single fund at time $t = 0$, which it must fully invest.[2] Four subsequent events happen in the life of the fund: 1) first-round investments are made, 2) the quality of those investments are realized, 3) second-round investments are made, and 4) payoffs are realized. The timeline is illustrated in Panel (a) of Figure 1. The size of the fund, F, is taken to be exogenous. After the fund is raised, two potential projects (indexed by i) arrive for first-round investments. At time $t = 1$ the venture firm learns the quality of the projects in which it made first-round investments and can then make second-round investments at time $t = 1\,{}^{1}\!/_{2}$. The payoff for a second-round investment is a function of the amount invested and the quality of the project. For an investment of size x_i in project i the payoff is given by $\theta_i f(x_i)$, where θ_i captures project quality. In what follows, I will assume this payoff function takes the form $f(x) = \sqrt{x}$. The discount rate will also be assumed to be zero.

First-round investment decisions are abstracted away from in the model by assuming the cost of these investments is zero. Thus, the venture firm will always choose to make first-round investments in both projects. This is done because I am primarily interested in continuation financing decisions on existing portfolio companies. In the single-fund case, it would be equivalent to think of the model as starting at time $t = 1$, with two existing portfolio companies and F dollars of uninvested capital remaining to invest in them.

At time $t = 1\,{}^{1}\!/_{2}$ the venture firm is assumed to maximize the terminal payoff of its investments, subject to the constraint that it must put all its capital to work. Thus, it solves

[2] In reality, it is not typically required that all committed capital be invested, but returning capital to limited partners is rare. This is most likely due to management fees that would be lost as well as the negative signal it would send about the venture firm's deal flow.

the problem:

$$\max_{x_i, x_j} \quad \theta_i \sqrt{x_i} + \theta_j \sqrt{x_j} \tag{2.1}$$

$$s.t. \quad x_i + x_j = F. \tag{2.2}$$

It is then straightforward to show that optimal investment is given by $x_i = F \frac{\theta_i^2}{\theta_i^2 + \theta_j^2}$, leading to a payoff of $v = \sqrt{F(\theta_i^2 + \theta_j^2)}$, where j indexes the project that is not i. In addition, it is easy to see that investment in i increases as the quality of project j decreases:

$$\frac{\partial x_i}{\partial \theta_j} = \frac{-2F\theta_i^2 \theta_j}{(\theta_i^2 + \theta_j^2)^2} < 0. \tag{2.3}$$

This is what was referred to earlier as reverse contagion. It occurs because the venture firm has a fixed amount of capital that it must invest. Thus, project i receives more capital when the prospects of project j decline, even if the prospects for project i remain unchanged. Here, the venture firm engages in *relative* evaluation.[3] One could think of project i as representing the non-IT portion of a generalist venture firm's portfolio, and project j as representing the internet portion. The collapse of the technology bubble would be represented in this simple model by a low realization of θ_j, leading to high investment in non-IT companies.

[3]This relates closely to the "bright side" view of internal capital markets. For theoretical work in this area, see Williamson (1975); Meyer, Milgrom, and Roberts (1992); Gertner, Scharfstein, and Stein (1994); Stein (1997); Scharfstein and Stein (2000); Rajan, Servaes, and Zingales (2000). For particularly related empirical work, see Lang, Ofek, and Stulz (1996); Lamont (1997); Shin and Stulz (1998); Rajan, Servaes, and Zingales (2000); Ozbas and Scharfstein (2010). Indeed, although diversified conglomerates are not generally considered financial intermediaries, venture capital firms do resemble them in some ways. However, there are limits to this analogy. First, venture firms cannot invest cash flows from one portfolio company into another. Second, venture-backed companies are generally free to raise follow-on rounds from any venture firm, whereas divisions of a conglomerate are legally bound to it.

2.2.2 A Two-Fund Venture Firm

Now I extend the model by assuming that at time $t = 1\,{}^1\!/\!_4$, after learning the quality of its existing portfolio companies, but before making second-round investments, the venture firm will raise a second fund (Fund II) of size F_{II}. The timing of events for the second fund is just like the first. Again, immediately after fundraising, first-round investments can be made in two new projects at zero cost. Then at time $t = 2$ the quality of these projects will be realized and second-round investments will be made, with payoffs occurring the following period. Panel (b) of Figure 1 illustrates the timing for both funds.

The only difference in Fund II is that uninvested capital left over from Fund I, $F_I - x_{i1} - x_{j1}$, can also be invested in its portfolio companies in the second round. However, capital from Fund II cannot be used to invest in Fund I portfolio companies. This is meant to reflect the cross-fund investing restrictions mentioned earlier. Now at time $t = 2\,{}^1\!/\!_2$ the venture firm solves the same constrained optimization problem as in the single-fund case, with uninvested capital of $F_{II} + F_I - x_{i1} - x_{j1}$. This means that the expected payoff from the fund's portfolio companies, as of time $t = 1\,{}^1\!/\!_2$, is given by $\mathbb{E}[v_2] = k\sqrt{(F_{II} + F_I - x_{i1} - x_{j1})}$, where $k \equiv \mathbb{E}[\sqrt{(\theta_{i2}^2 + \theta_{j2}^2)}]$. Understanding this, the venture firm now solves the following problem at time $t = 1\,{}^1\!/\!_2$:

$$\max_{x_i, x_j} \quad \theta_{i1}\sqrt{x_{i1}} + \theta_{j1}\sqrt{x_{j1}} + k\sqrt{(F_{II} + F_I - x_{i1} - x_{j1})} \tag{2.4}$$

$$s.t. \quad x_{i1} + x_{j1} \leq F_I. \tag{2.5}$$

In this case, when the inequality constraint is non-binding, optimal investment is given by:

$$x_{i1} = \frac{(F_{II} + F_I)\theta_{i1}^2}{k^2 + \theta_{i1}^2 + \theta_{j1}^2} \tag{2.6}$$

$$\Rightarrow \frac{\partial x_{i1}}{\partial \theta_{j1}} = \frac{-2(F_{II} + F_I)\theta_{i1}^2 \theta_{j1}}{(k^2 + \theta_{i1}^2 + \theta_{j1}^2)^2} < 0. \tag{2.7}$$

When the inequality constraint is binding, optimal investment is the same as in the one-fund case.

Proposition 1. *In the two-fund case without performance-sensitive fundraising, reverse contagion (*$\frac{\partial x_{i1}}{\partial \theta_{j1}} < 0$*) still occurs in the region of the parameter space in which the inequality constraint is non-binding; however, it is mitigated (the magnitude of* $\frac{\partial x_{i1}}{\partial \theta_{j1}}$ *is lower than in the one-fund case).*

Proof. See Appendix A. □

The intuition behind this proposition is straightforward, as the capital that is not invested in project j can now be saved for next period rather than needing to be invested immediately in project i. Thus, future fundraising/investing can dampen the degree of reverse contagion.

2.2.3 A Two-Fund Venture Firm with Performance-Sensitive Fundraising

Now I allow F_{II} to be a function of the average quality of projects realized in period 1: $F_{II} = b(\frac{\theta_{i1}+\theta_{j1}}{2})$. This is a reduced form way of capturing the idea that limited partners will be more reluctant to invest in a follow-on fund if the previous fund appears to have poor interim performance (Kaplan and Schoar, 2005). This could be incorporated into a richer model by allowing limited partners to learn about the talent of general partners through interim performance. The parameter, b, above, captures the flow-to-performance sensitivity of a venture firm. In this case, when the inequality constraint is non-binding, optimal investment at time 1 will be given by:

$$x_{i1} = \frac{(b(\frac{\theta_{i1}+\theta_{j1}}{2}) + F_I)\theta_{i1}^2}{k^2 + \theta_{i1}^2 + \theta_{j1}^2} \tag{2.8}$$

$$\Rightarrow \frac{\partial x_{i1}}{\partial \theta_{j1}} = \frac{\theta_i^2(b(k^2 + \theta_i^2 - 2\theta_i\theta_j - \theta_j^2) - 4F_I\theta_j)}{2(k^2 + \theta_{i1}^2 + \theta_{j1}^2)^2}. \tag{2.9}$$

Proposition 2. *In the two-fund case with performance-sensitive fundraising, there exists b^* such that for $b > b^*$ ordinary contagion occurs ($\frac{\partial x_{i1}}{\partial \theta_{j1}} > 0$) in the region of the parameter space in which the inequality constraint is non-binding.*

Proof. See Appendix A. □

Thus, for a venture firm whose fundraising is sufficiently sensitive to performance, investment in project i can now decline with the realized quality of project j. The reason is that the decreased quality of project j leads to a smaller second fund. This decline in total resources creates a force for decreased investment in both existing projects, which can outweigh the increased relative attractiveness of project i with respect to project j. This is true even despite the assumed cross-fund investing restrictions. Moreover, while the cross-fund investing restrictions in the model allow Fund I to invest in the second-round of Fund II projects, even this is not critical. For example, one could think of the second-round investments at time $t = 2\,{}^1\!/_2$ as first-round investments and all of the results would remain unchanged. Intuitively, what is important is that some of the capital that would have gone into new projects from the new fund will now come from the old fund. Indeed, as long as funds overlap temporally, there will always be semi-fungibility across funds, regardless of restrictions.

2.3 Lock-in

While venture firms with high exposure to a depressed sector may indeed reduce the supply of capital to unrelated clients, it does not necessarily follow that companies affiliated with these investors should be harmed. If such companies were able to switch costlessly to another venture firm, they would be unaffected by the poor performance of others originally held in the same portfolio. However, there are several reasons why it may be difficult/costly to switch venture firms or more generally to raise a new round of financing without the participation of investors from the previous round.

Previous investors in a company accumulate a large amount of private information. This is likely to be especially true in the context of venture capital, as venture investors are known to be deeply involved in the operations of their portfolio companies[4]. Given this, competing venture firms face a form of the winner's curse in bidding against a better-informed incumbent, making it difficult for portfolio companies to switch capital providers, much as in Sharpe (1990) and Rajan (1992). Of course, if it were known that an incumbent ceased investing in one of its portfolio companies due to unrelated financial difficulties, the winner's curse would no longer be in operation. It is not clear, however, that competitors are fully aware of the details of one another's financial health, especially as venture firms do not fail abruptly, due to the long-term nature of limited partner commitments. To the extent that a venture firm that is perceived to be in trouble continues investing in some companies but not others, there will still be a winner's curse.

Finally, even absent the winner's curse, it remains true that much valuable information is likely destroyed when relationships between venture firms and portfolio companies dissolve. For example, suppose a company were known by its founders and original investors to be

[4]See e.g. Lerner (1995); Hellmann and Puri (2000, 2002); Baker and Gompers (2003); Kaplan and Strömberg (2004)

of high quality, but its original investors could no longer continue to support it for reasons known by all to be unrelated to the company itself. In this case, new investors would still have to value the company as one of merely average quality. At such a valuation, the founders' participation constraints may not be satisfied, or they may be so diluted that they would not have proper incentives. While in this case the original investors would like to transmit their knowledge to another venture firm, such communication would not be credible given the soft nature of their information and their incentives as existing shareholders.

3 Empirical Strategy

To investigate contagion among portfolio companies in venture capital, I examine continuation financing outcomes for venture-backed non-IT companies during the period surrounding the collapse of the technology bubble. In particular, I exploit variation in the degree of venture firms' exposure to the internet sector. Again, this variation exists largely due to the fact that some firms specialize in non-IT investments, while others make both IT and non-IT investments. I will sometimes refer to generalist firms with high internet exposure as "internet-focused venture firms." However, note that the most internet-focused firms, many of which became somewhat infamous in the wake of the bubble, will not be included in the analysis. This is because I consider only firms that made at least some non-IT investments.

The most basic specification can be thought of as analogous to a difference-in-differences estimation framework. Here, the treatment effect of interest is that of being held in the same portfolio as many internet companies. A company is, thus, considered to be in the treatment group if its investors had high internet exposure at the peak of the bubble and in the control group if they had low exposure. The pre- and post- periods are defined as the three years preceding and following the peak, respectively. The outcome of interest is the likelihood of a portfolio company receiving a follow-on round of financing. One approach would be to estimate a discrete response model with a dependent variable equaling one if a company, i, considered for continued financing at time t received a follow-on round. The difficulty with this approach is that, for companies that did not receive a follow-on round, the time t at which they were considered and rejected is unknown. Furthermore, regardless of whether the company was ultimately accepted or rejected for continued financing, it is somewhat unrealistic to think of deliberation over this decision as having taken place at one particular date.

To address these challenges, I instead estimate Cox proportional hazards models of the form,

$$h_{ijt}(\tau) = h_0(\tau)\exp(\beta_1 Post_t + \beta_2 InternetVC_{ij} + \beta_3 Post_t \times InternetVC_{ij} + \boldsymbol{x}_{ijt}\boldsymbol{\beta}), \quad (3.1)$$

where i indexes portfolio companies, j indexes rounds of financing, and t indexes calendar time. The variable τ represents analysis time, which is defined as the time since company i raised its previous round. The variables $InternetVC_{ij}$ and $Post_t$ are the treatment and post indicators, respectively, while $\boldsymbol{x_{ijt}}$ represents a vector of controls. Using the language of survival analysis, a spell is defined at the company-round level, and an event is defined as the raising of a follow-on round. The outcome being modeled, $h_{ijt}(\tau)$, is continuation hazard as a function of analysis time, conditional on covariates. To be more precise, the hazard function is defined as the limiting probability that an event occurs in a given time interval (conditional upon its not having occurred yet at the beginning of that interval) divided by the width of the interval:

$$h(\tau) = \lim_{\triangle\tau\to 0} \frac{\Pr(\tau + \Delta\tau > T > \tau | T > \tau)}{\Delta\tau}, \quad (3.2)$$

where T represents the time to the event. The key assumption of the Cox proportional hazards model is that all covariates simply shift some baseline hazard function $h_0(\tau)$ multiplicatively. With these assumptions, it is then possible to estimate the β parameters of the model, while leaving the baseline hazard function unspecified. Thus, no assumptions regarding the shape of the baseline hazard function are needed. This is the sense in which the model is semi-parametric. To fix ideas, however, one could think of this function as conforming to an inverted "U" shape. Immediately following a round of financing, it is initially unlikely that another round will be raised. Then, over time, this becomes increasingly likely, until eventually it becomes less and less likely, as the fact that the company has not received another round begins to indicate that it will never receive one.

Again, an event in this case is defined as a follow-on round occurring. However, there are also competing events in this context, which alter the probability of the event of interest (Gooley, Leisenring, Crowley, and Storer, 1999). In particular, before a company raises another round of financing, it may first go defunct, go public, or get acquired; in these cases no further rounds will occur. In these cases I censor the spell at the competing risk date.[5]

An alternative way of writing Equation 3.1 would be

$$\ln(h_{ijt}(\tau)/h_0(\tau)) = \beta_1 Post_t + \beta_2 InternetVC_{ij} + \beta_3 Post_t \times InternetVC_{ij} + \boldsymbol{x}_{ijt}\boldsymbol{\beta}. \quad (3.3)$$

The term $\ln(h_{ijt}(\tau)/h_0(\tau))$ is known in survival analysis as the log relative hazard or risk

[5]An alternative strategy would be to estimate a competing risks model such as that introduced by Fine and Gray (1999). However, despite the presence of competing risks, a Cox proportional hazards model (with censoring at competing risk dates) is better-suited in this setting. As pointed out by Pintilie (2007), this approach (termed "analysis of cause-specific hazard") is appropriate when one is interested in isolating the causal impact of a variable on the hazard of an event occurring. Competing risk models, on the other hand (termed "analysis of the hazard of subdistribution"), are appropriate when one is interested in understanding cumulative incidence. To see this distinction, suppose one were interested in the relationship between smoking and cancer, but smoking often causes death to occur before the development of cancer. In the extreme case, smoking may then actually reduce the cumulative incidence of cancer, even though a positive causal relationship exists.

score. This transformation demonstrates that the Cox model is essentially linear in nature. In particular, marginal effects in this model do not depend on the value of other covariates as they do in logit/probit models. Coefficients are typically reported raw or exponentiated to facilitate a hazard ratio interpretation.[6]

The two key assumptions underlying the difference-in-differences methodology are that, absent any treatment, 1) the change (from pre- to post-) for the treatment group would have been the same as for the control group, and 2) any difference in the outcome variable that existed for the two groups in the pre-period would have persisted in the post-period. Thus, absent the treatment, the expected hazard for a company funded by an internet-focused syndicate would have been

$$h_{ijt}(\tau) = h_0(\tau)\exp(\beta_1 + \beta_2), \tag{3.4}$$

but actual expected hazard is given by

$$h_{ijt}(\tau \mid InternetVC_{ij} = 1, Post_t = 1) = h_0(\tau)\exp(\beta_1 + \beta_2 + \beta_3). \tag{3.5}$$

The percent change in expected hazard due to treatment is, thus, $exp(\beta_3) - 1$. This can be thought of as analogous to the normal difference-in-differences estimator. If internet-focused venture firms became troubled in the post-bubble period and were more selective about making disbursements to portfolio companies as a result, one would expect this coefficient to be negative. Of course, treatment here is not actually binary. The extent of a venture firm's exposure to the internet sector is in fact continuous. Recognizing this, I also estimate the above model, replacing the binary treatment variable $InternetVC_{ij}$ with the continuous variable, $InternetExposure_{ij}$, upon which it is based. I also estimate the model replacing the

[6] Relatedly, interaction terms also do not depend on the value of other covariates and can be meaningfully interpreted in a Cox model without the difficulties highlighted by Ai and Norton (2003) in the logit/probit context.

binary variable $Post_t$ with the continuous variable $log(InternetFlows_t)$, which represents aggregate flows to internet funds during the quarter corresponding to time t. The details concerning the construction of these variables will be discussed in greater detail in the next section.

The primary concern with the identification strategy outlined thus far is the potential endogeneity of $InternetExposure_{ij}$. Companies financed by venture firms with high internet exposure might also have experienced a decline in their prospects coinciding with the collapse of the technology bubble. Clearly, this would be the case if internet-focused venture firms also tended to invest in portfolio companies in related IT sectors such as computer software or communications, which is likely.

I address these endogeneity concerns in several ways. First, as previously described, I restrict the sample to include only non-IT portfolio companies. These companies largely operate in sectors such as biotechnology and energy, which have little direct connection with the types of technologies that were driving the technology bubble. Thus, limiting the sample to non-IT companies largely eliminates the possibility that the magnitude of the estimated β_3 coefficient is biased by the omission of a variable representing something akin to internet-relatedness, with which $InternetExposure_{ij}$ might be positively correlated. Instead, the concern would be that the prospects of non-IT companies that were backed by venture firms with high internet exposure tended to decline in the post-bubble period due to other omitted/unobservable characteristics.

Perhaps the most obvious potential candidate for such a characteristic is geography. For example, if venture firms with high internet exposure tended to be located in Silicon Valley and invested in portfolio companies near their headquarters, it may be that their non-IT portfolio companies suffered a greater decline due to the decline in the local economy. To account for this possibility, I include fixed effects for 13 regions (including Northern

California), as well as interactions between these fixed effects and the $Post_t$ indicator variable, to control for the fact that companies in different regions might have felt differential effects of the collapse of the technology bubble. Similarly, I include a full set of fixed effects for the sector and stage of development of the portfolio company, as well as interactions between those fixed effects and the $Post_t$ indicator. While this would seem to cover the most obvious potentially omitted variables, it is of course still possible that non-IT companies backed by internet-focused venture firms differed along some unobservable dimension that would account for their greater decline in the post-bubble period.

To address this remaining possibility, I exploit the fact that companies can have relationships with multiple venture firms. This allows me to run related tests that include company fixed effects. Identification in this case is based on within-company variation in investor internet exposure. Thus, I am able to examine whether the same company was less likely to receive continuation financing from those of its investors that had greater exposure to the internet sector. Such a result could not be explained by unobservable company characteristics. Rather, it would suggest a decrease in the supply of capital from investors with high internet exposure.

4 Data

The data used in this study come from the Thomson-Reuters VentureXpert database. These data contain information on both venture capital financing rounds (including the round date, the identities of the venture firms and portfolio company participating, and the size of each venture firm's contribution to the round), and venture firm fundraising (including the size and closing date of all funds raised by a firm). I restrict the sample to venture capital financing rounds involving U.S. portfolio companies. In addition, only companies that are categorized by Thomson as non-IT are included. Finally, I also include only rounds that were backed by venture capital organizations structured as autonomous partnerships. Thus, rounds backed entirely by individuals, or entities such as corporate-sponsored venture funds, are omitted.

The estimation window runs from March 31, 1997, to March 31, 2003. Some spells begin before the estimation window, but end during the estimation window. Likewise, some spells begin during the estimation window, but end after the window. These spells are censored appropriately at the boundaries. In addition, as mentioned earlier, spells are also censored at competing risk event dates (when a company goes defunct, goes public, or gets acquired). In some cases, particularly for companies that ultimately went defunct, the date of the competing risk event is unknown. In these cases, I censor the spells at two years after the last observed financing round. The results are not sensitive to this assumption.

Another issue with the data, previously reported by Lerner (1995), is that some companies appear to have too many financing rounds recorded. This is likely due to staggered disbursements from a single round being misrecorded as multiple rounds. Also, a small number of companies have consecutive rounds that are extremely far apart. I, thus, restrict the sample to companies with rounds no less than 30 days and no more than six years apart. Again, the results change little if these companies are included.

4.1 Key Measures

4.1.1 Dating the Peak

The post-bubble period, in which the $Post_t$ indicator variable is set equal to one, is defined as all dates following March 31, 2000. This is motivated by Figure 2, which shows the buy-and-hold return on publicly traded internet stocks. Internet stock returns are calculated as in Brunnermeier and Nagel (2004) and Greenwood and Nagel (2009), using a value-weighted portfolio of stocks in the highest NASDAQ price/sales quintile, rebalanced monthly.[7] Quarterly flows to newly raised venture funds are also shown, both for all funds and internet-specific funds, as categorized by Thompson-Reuters.[8] Commitments are converted to real 2000 dollars using the GDP deflator. The dotted vertical line in the figure corresponds to March 31, 2000, which is the peak of all three series. Thus, not only did internet stocks peak at this date, but so did venture capital fundraising. The estimation window is chosen accordingly to run from three years prior to the peak (the pre-period) to three years following the peak (the post-period).

4.1.2 Measuring Internet Exposure

The degree of a venture capital firm k's exposure to internet investments, $InternetExposure_k$, is measured as the percentage of the total amount invested by the firm that was disbursed to companies operating in the internet sector during the 10 years leading up to the peak. A 10-year window is chosen as this is the life of a typical venture fund, although results are similar if a shorter window is used. To limit the effect of outliers that may occur due to firms with few investments in the data, firms with less than five observed investments during this period are considered to have unknown internet exposure.[9]

[7]As Greenwood and Nagel explain, this methodology is used because SIC codes fail to identify the bubble segment of the market in many cases. For example, the internet stock eBay has SIC code 738, which places it in the Business Services industry.

[8]Note that internet-specific fund flows do not fully reflect the amount of money raised by venture capital firms for internet investments, as many funds made substantial internet investments, but were not categorized as internet-specific funds.

[9]Note that this measure of internet exposure includes investments in companies that went public, were acquired, or went defunct prior to the peak. An alternative approach would be to look only at a firm's active portfolio as of March 31, 2000, to determine its internet exposure. Trying to isolate active portfolio companies at the peak, however, is somewhat complicated again by the fact that the date of failure for defunct companies is usually unknown. Another complication is that lockup provisions typically restrict venture firms from selling their shares for some period of time following an IPO. In any case, it is not clear that this is conceptually the measure of interest, as even if a venture firm did not hold many active internet companies in its portfolio at the peak of the bubble, if it were perceived as an internet specialist due to its investment history, it would likely have faced difficulty raising a new fund in the post-bubble period regardless.

Funding rounds are often financed by syndicates of multiple venture firms. In this case internet exposure is defined at the syndicate level. Specifically, for the syndicate backing the jth round of company i, internet exposure is defined as 1) the mean of $InternetExposure_k$ for all venture firms participating in the round, weighted by their contribution to the round and 2) the value of $InternetExposure_k$ for the lead investor in the round. For the first measure, internet exposure is weighted by firm contribution rather than firm assets under management because a portfolio company would likely be most adversely affected if its primary investor were in trouble, even if that investor were not the largest in the syndicate based on assets under management. For the second measure, the lead venture firm is taken to be the one that has invested in the company the longest, as in Gompers (1996). Ties are broken by the total amount invested in the company, inclusive of the current round. Using this definition, a lead venture firm cannot be uniquely identified in some cases and is then simply considered to be unknown.

4.1.3 Non-IT Classification

Finally, one potential concern with these data is that companies may be classified as non-IT, when in fact they make use of technologies related to the bubble. For example, one may worry that a company like WebMD, a website that provides health information for patients, may be considered to be in the health sector and therefore categorized as a non-IT company. Importantly, Thomson does not make the IT/non-IT distinction based on sub-sector; rather, this depends on a company's use of technology. Thus, not all health-related companies are considered non-IT. In particular, Thomson provides six sector classification variables that range from very coarse (3 categories) to very detailed (570 categories). According to these variables, WebMD is classified as 1) "Information Technology," 2) "Computer Related," 3) "Internet Specific," 4) "Internet Specific," 5) "Internet Content," and 6) "Medical/Health

Info/Content." In contrast, there are other "Medical/Health Info/Content" companies in the data that are classified as non-IT. The high level of detail contained in these classifications, as well as the fact that the IT/non-IT distinction is not based solely on sub-sector variables, gives some comfort that the non-IT classifications are at least largely correct. In addition, Thomson provides detailed business descriptions, product key words, and technology class descriptions. Results are robust to excluding companies that might be considered more likely to be IT-related based on these variables. In addition, when company fixed-effects are included, they control for unobservable IT-relatedness.

4.2 Summary Statistics

After the sample restrictions described above are imposed, I am left with observations on 782 venture firms, funding 6,104 rounds of 3,263 companies. Table 1 shows the composition of the sample both in terms of companies and rounds.[10] Rounds are the relevant unit of observation in most of the analysis to follow in the next section. Panel (a) breaks down the sample by region. As speculated earlier, rounds backed by venture firms in the top quartile of internet exposure ($InternetVC_{ij} = 1$) are much more likely to be associated with portfolio companies located in Northern California than rounds in the bottom quartile ($InternetVC_{ij} = 0$). The differences in the regional distributions are confirmed by a chi-square test. Panel (b) shows the breakdown of companies by sector. Life sciences companies operating in the medical/health and biotechnology sectors account for more than half of the observed financing rounds.

Finally, Panel (c) breaks the sample down by stage. In this case, only the round level is shown, as companies change stages from round to round. The order of the stages from least developed to most are startup/seed, early, expansion, and later. By far, the most

[10]These differ as the average company in the sample received nearly two rounds of financing.

common stage financed is the expansion stage with slightly more than 50% of observed rounds occurring at this stage.

Summary statistics of the key variables used in the analysis are presented in Table 2. These statistics are presented at varying units of observation as appropriate. For example, the internet exposure of syndicates backing rounds is shown at the round level. As described earlier, this is measured for the whole syndicate as well as the lead venture firm in the syndicate.[11] Both measures of internet exposure appear to be distributed similarly with a mean of nearly 19%. Thus, the average round in the sample was backed by venture firms that made 19% of their total disbursements to internet companies in the decade leading up to the peak of the bubble. The mean number of investors in a round was slightly less than three. The distribution of internet exposure is also shown at the venture firm level. The average venture firm had internet exposure of 24%, indicating that lower exposure companies must have funded more rounds in the data. Though not shown in the table, the modal internet exposure in this sample of firms making non-IT investments was zero, with slightly more than 20% of firms having no internet investments at all. As stated earlier, internet exposure is based on observed investments in the 10 years leading up to the peak. The average firm in the sample had almost 60 observed investments during this period.

5 Results

5.1 On Average, IT Companies Affected, Non-IT Companies Unaffected

I begin by verifying that IT companies, and particularly internet companies, had greater difficulty raising continuation financing in the post-bubble period. Were this not the case, it

[11] When the lead venture firm cannot be uniquely identified, the former may be known while the latter is not. When the round contributions of firms in the syndicate are not recorded in the data, the reverse may be true.

would seem unlikely that non-IT companies backed by more internet-focused investors would have experienced negative effects from the collapse of the bubble. I estimate univariate Cox models of the form

$$h_{ijt}(\tau) = h_0(\tau)\exp(\beta_1 Post_t) \tag{5.1}$$

for each IT sector in the data. Results are shown in Panel (a) of Table 3. Standard errors are clustered by portfolio company. The implied percent change in hazard from before to after the peak, $exp(\beta_1) - 1$, is shown below the raw coefficients. For companies in most of the IT sectors, the hazard of raising a continuation round was considerably lower in the post-bubble period. In particular, companies in the communications, hardware, and software sectors experienced a decrease in hazard of more than 20%. As expected, companies in the internet sector were hit the hardest. Internet companies are estimated (with high precision) to have had a decrease in hazard of more than 50%.

The results for non-IT sectors are shown in Panel (b). Companies in non-IT sectors did not, on average, suffer major declines. At conventional level of significance, biotech, consumer, energy, medical, and other non-IT companies all had a statistically insignificant change in hazard in the post-bubble period. Moreover, noisy point estimates indicate a less than 10% decline in all non-IT sectors except energy, which is estimated to have had nearly a 9% increase. While interesting to note, this is not necessary for my identification strategy to be valid, as I will be comparing the experience of non-IT companies backed by investors with high and low internet exposure. Put differently, the difference-in-differences methodology does not require that the control group be unchanged in the post-period.

5.2 Non-IT Companies Backed By Internet VCs Were Affected

5.2.1 Difference-in-Differences, Extreme Quartiles

Next, I limit the sample to non-IT companies and estimate the difference-in-differences specification of Equation 3.1. The treatment indicator variable, $InternetVC_{ij}$, is set equal to one if $InternetExposure_{ij}$ (for the venture firms backing the jth round of company i) is in the top quartile of all rounds. The treatment indicator is set equal to zero if $InternetExposure_{ij}$ is in the bottom quartile. Rounds in the middle two quartiles are omitted under this specification because it is difficult to discretely categorize rounds with $InternetExposure_{ij}$ near the median as either treated or untreated. Referring to the summary statistics presented in Table 2, the 25th percentile of $InternetExposure_{ij}$ is between 5% and 7%, depending on how the exposure of a syndicate is measured; the 75th percentile is around 27%.

Table 4a reports the results. Standard errors are clustered by portfolio company in the first three columns as well as by lead firm in the last three columns (Cameron, Gelbach, and Miller, 2011). The estimated percent change in hazard due to treatment, $exp(\beta_3)-1$, is shown below the raw coefficients. Beginning with Column (1), the estimate of β_3 is negative and statistically significant. The magnitude of the coefficient implies a decline in continuation hazard of 31% due to treatment. Thus, the estimated effect is quite substantial. The coefficient on $InternetVC_{ij}$ is also positive and statistically significant under this specification. This suggests that, relative to other non-IT companies, those backed by internet-focused syndicates had less difficulty raising follow-on rounds before the collapse. This will be explored in more depth, but turns out not to be as robust as the main finding.

Again, with the proportional hazards assumption, the baseline hazard function is left unspecified. However, given the estimated β coefficients, a smoothed estimate of the implied baseline hazard function can be backed out. It is useful to examine the shape of this function to ensure that it is reasonable. Figure 3 shows the hazard functions derived from Column (1) of Table 4a. The proportional shifts in the baseline hazard, shown at various values of the covariates, simply reflect the estimated coefficients just discussed. As speculated earlier, it does appear that the baseline hazard function conforms to an inverted "U" shape. The figure shows graphically that non-IT companies backed by internet-focused syndicates experienced a decrease in continuation hazard in the post-bubble period (Panel a), whereas those backed by non-internet syndicates experienced a statistically insignificant increase (Panel b). The difference in these differences is the estimated treatment effect.

Another way of understanding the economic magnitudes implied by these estimates is to examine the implied survivor function, $S(\tau) = \Pr(T > \tau)$, which reports the probability of an event not having occurred yet as of time τ. In this case, a portfolio company would be said to have "survived" until time τ if it had not received continuation financing as of that time. Intuitively, downward shifts in the hazard function correspond to upward shifts in the survivor function. In fact, there is a one-to-one inverse relationship between cumulative hazard and the survivor function.

Figure 4 shows how the survivor function shifted for the treatment and control groups, again based on Column (1) of Table 4a. Examining the survivor function is useful, as it provides magnitudes that are perhaps more easily interpreted. For example, the estimates imply that, after five years, the probability of not having yet raised a follow-on round increased by 8.3% for the treatment group and decreased by 4.1% for the control group. As discussed earlier, going too long without a follow-on round of financing typically leads venture-backed companies to go defunct. Thus, in terms of real effects, these estimates likely imply that companies in the treatment group had a significantly larger increase in their failure rate.[12]

[12]Ideally, this could be tested more directly. However, conducting such a test is difficult for two reasons. First, company failure dates are often unknown. Second, liquidations are often coded in the data as acquisitions rather than failures. Thus, it is difficult to assess both whether a company failed and, if it failed, when the failure occurred.

In Column (2) of Table 4a, company stage, region, and sector fixed effects are added to the specification. In Column (3), I allow interactions between the company controls and the $Post_t$ indicator. As previously discussed, this is important, as companies with certain characteristics might have been both more adversely affected by the collapse of the bubble and also more likely to have been funded by a more internet-focused syndicate. After adding these controls, the estimated treatment effect remains large and statistically significant. Moreover, the small change in the point estimates between Columns (2) and (3) suggests that the results in the previous columns were not driven by a tendency for more internet-focused firms to have invested in non-IT companies with observable characteristics that made them worse investments after the bubble. It remains possible that unobservable characteristics of this kind are driving the results. This will be addressed shortly. In Columns (4) through (6), I estimate the same specifications as in the first three columns, but define the variable $InternetVC_{ij}$ based on the internet exposure of only the lead venture firm in the round. This gives rise to similar results.

Next, I estimate the same regressions, substituting the continuous variable $InternetExposure_{ij}$ for $InternetVC_{ij}$ and making use of the entire sample. This takes advantage of the fact that treatment is not actually binary in this case. Results are reported in Table 4b and are very similar to the previous panel. To interpret the magnitudes of these estimates, note that the percent change in hazard associated with the end of the bubble is equal to $\exp(\beta_1 + \beta_3 InternetExposure_{ij}) - 1$. Substituting the coefficients from Column (1), this expression evaluates to -15.8% for a portfolio company backed by venture firms with mean internet exposure (of 24.4%). For a portfolio company backed by venture firms with $InternetExposure_{ij}$ one standard deviation above the mean (47.9%), the collapse of the bubble was associated with a -33.4% change, or a 17.6% larger decrease in hazard. In the remaining specifications, this difference is similar, ranging from 14.3% to 17.2%. So again, the magnitude of the estimated effect is substantial.

Finally, I also estimate these equations once more on the whole sample, substituting the variable $\log(InternetFlows_t)$ for $Post_t$, where $\log(InternetFlows_t)$ represents the log of all flows to internet-specific venture capital funds raised in the quarter corresponding to time t. Thus, instead of defining discrete pre- and post- periods, this specification takes advantage of the continuous variation over time in the perceived prospects of young internet companies, as reflected by flows into internet-specific funds. Results are reported in Table 4c, with standard errors now clustered also by quarter. Across all six specifications, there is an estimated positive and statistically significant interaction between $\log(InternetFlows_t)$ and $InternetExposure_{ij}$, providing evidence that non-IT companies backed by venture firms with greater internet exposure were more sensitive to fluctuations in the internet sector. Note that β_1 is also statistically insignificant across all six specifications, which suggests that non-IT companies backed by venture firms with no internet exposure were not sensitive at all to these fluctuations.

5.2.2 Additional Robustness Tests

One concern at this point is that some of the companies classified by Thomson as non-IT may in fact have been IT-related. If this were the case, it might simply add noise to the results, without introducing any systematic bias. However, bias would be introduced if non-IT portfolio companies backed by venture firms with internet investments tended to be miscatergorized as non-IT more frequently. Another related concern is that, even if no companies were misclassified, those backed by more internet-focused investors may have had other unobservable characteristics that caused their prospects to decline when the bubble burst. Both of these possibilities will be addressed shortly by examining portfolio companies with multiple investors and including company fixed effects. The miscategorization problem can also be examined, however, by repeating the above analysis on sub-samples that are less likely to include IT-related companies. This is done in Table 5. Column (1) of this table replicates Column (6) of Table 4b, excluding all non-IT companies classified by Thomson as "Consumer Related." Similarly, Column (2) excludes all non-IT companies producing "Other Products." Column (3) excludes all non-IT companies with variations of the words "Internet," "Online," "Web," "E-Commerce," "Software," "Digital," "Electronic," "Computer," "E-mail," "Hardware," or "Network" in their detailed business description, product keywords, or technology description. In Column (4), companies that are categorized as IT by Dow Jones' VentureSource database are excluded.[13] In all four sub-samples, the coefficient on $Post_t \times InternetExposure_{ij}$ continues to be negative and statistically significant. Thus the effect continues to be strongly present, even in sub-samples that are less likely to contain IT-related companies.

5.3 Continuation Hazard Did Not Increase as Bubble Inflated, Decreased as Deflated

The results thus far suggest that the decline in a company's continuation hazard when the bubble burst was greater the greater the internet exposure of its investors. It is not clear, however, whether this greater decline in continuation hazard primarily reflected hazard being "too high" during the bubble period or "too low" during the post-bubble period. Put another way, contagion among portfolio companies may have taken place both on the upside as well as on the downside. In general, it is not possible to distinguish between these two scenarios using a difference-in-differences framework. It is possible, however, to shed some light on this issue using the quarterly flows specification. In particular, if contagion occurred on the upside, one would expect continuation hazard to have increased along with $InternetFlows_t$

[13] VentureSource is another major venture capital database. Portfolio companies are matched using a combination of name, address, phone number, and URL.

as the bubble inflated. To test whether this occurred, I re-estimate the specifications of Table 4c, now allowing the interaction between internet flows and venture firm internet exposure to differ before and after the peak of the bubble. Results are reported in Table 6. In all specifications, the estimated interaction in the pre-period is statistically insignificant. This suggests that, as the bubble inflated, non-IT portfolio companies did not become more likely to receive follow-on rounds, even if their venture firm was heavily invested in the internet sector. By contrast, the estimated interaction in the post-period is positive and statistically significant across all specifications. This suggests that, as the bubble deflated, portfolio companies did become less likely to receive follow-on rounds, particularly if their venture firm was heavily invested in the internet sector. On the whole, these results provide evidence that contagion among portfolio companies primarily occurred on the downside.

5.4 For Same Company, Internet VCs Became More Likely to Drop Out of Rounds

It still remains possible that non-IT companies backed by more internet-focused venture firms differed from others along some unobservable dimension that made them worse investments in the post-bubble period. In this case, these companies may have had more difficulty raising continuation financing, not because they were held in the same portfolio as internet companies, but because their own future prospects deteriorated alongside those of internet companies. To investigate whether the previous results are driven by unobservable company characteristics of this kind, I run related tests that include company fixed effects. It is possible to include these fixed effects because, as noted earlier, venture-backed companies frequently take capital from multiple investors. Identification in this case is based on within-company variation in investor internet exposure. Thus, I am able to examine whether the *same company* was less likely to receive continuation financing from those of its investors that had greater exposure to the internet sector. Such a result could not be explained by demand-side factors, i.e. company characteristics. Rather, it would suggest a decrease in the supply of capital from investors with internet-heavy portfolios.

To address these issues, I run related tests that do not make use of the proportional hazards framework. Instead, I limit attention to rounds that were actually raised, and estimate whether previous investors with high internet exposure were more likely to drop out of these rounds after the bubble burst. This can be thought of as relating to the intensive margin (i.e. conditional on raising a round, did investors continue to participate?), whereas previous results related to the extensive margin (i.e. was a round raised from any investor?). For each continuation round raised by a company, I form an observation for each venture firm that participated in the previous round. If the venture firm participated in the current round, $VCDropout_{ijkt}$ is equal to zero; otherwise, $VCDropout_{ijkt}$ is equal to one.[14]

I then estimate linear probability models of the form,

$$VCDropout_{ijkt} = \alpha_i + \beta_1 Post_t + \beta_2 InternetExposure_k + \beta_3 Post_t \times InternetExposure_k, \tag{5.2}$$

where α_i represents a company fixed effect. Observations in this case are at the company-round-VC level (k indexes VCs). The primary coefficient of interest is again β_3. If estimated to be positive, this would indicate that greater internet exposure was associated with a greater increase—from before to after the peak of the bubble—in the probability of dropping out of a round.

Table 7 reports the results. As $InternetExposure_k$ varies only at the venture firm level, standard errors are clustered accordingly by venture firm as well as portfolio company. In

[14]One exception to this rule is made if the venture firm is observed participating again in subsequent rounds of the company. Then, the firm is considered a participant in the current round, as its omission is taken to be a data error.

the first two columns, Equation 5.2 is estimated via OLS without company fixed effects. In the final two columns, company fixed effects are included. Across all specifications, β_3 is estimated to be positive and statistically significant, with point estimates decreasing only slightly with the inclusion of company fixed effects. The coefficients in the final column imply that a one standard deviation increase in internet exposure was associated with a 4.16% larger increase in the probability of dropping out of a round after the bubble burst. Considering that the unconditional probability of a firm dropping out in the pre-period was only 10.8%, these magnitudes are again economically meaningful, as they represent a percentage increase of 38.5. This provides perhaps the clearest evidence that more internet-focused venture firms ceased supporting companies that they would have liked to continue to support.[15]

Finally, it should be said that these results do imply that some companies were able to overcome lack of participation from previous investors. However, there is no inconsistency between these findings and those presented previously. Indeed, if none were able to overcome investor dropout, results would be found only on the extensive margin. Similarly, if all were able to do so, results would be found only on the intensive margin.

5.5 Internet VCs Had Increased Fundraising Difficulty After Collapse

Next, I explore the mechanism underlying these results. As discussed earlier, the most obvious mechanism through which ordinary contagion might occur is through the transmission of fundraising difficulties. It seems quite plausible that venture firms with internet-heavy portfolios would have had trouble raising new funds from limited partners after the bubble burst. To investigate this, I estimate the same hazard models as before, but now at the

[15]Note that β_2, the coefficient on $Post_t$, is estimated to be negative without company fixed effects and positive with company fixed effects. This is likely due to selection, as companies that received follow-on rounds in the post-bubble period may have been of higher quality and thus experienced fewer investor dropouts.

venture firm level. Specifically, rather than estimating the hazard of a portfolio company raising a continuation round from venture firms, I now estimate the hazard of a venture firm raising a follow-on fund from limited partners. In the three columns of Table 8, I repeat the three specifications of Table 4 at the venture firm level. Standard errors are clustered by venture firm and also by quarter in the third column.

The same general pattern emerges as at the portfolio company level. The coefficients on the interaction terms $Post_t \times InternetVC_k$ and $Post_t \times InternetExposure_k$ are both estimated to be negative, while the coefficient on $\log(InternetFlows_t) \times InternetExposure_k$ is estimated to be positive; all are statistically significant. This suggests that the adverse effect of the collapse of the technology bubble on fundraising was greater for venture firms that were more associated with internet investing. The magnitudes of these estimates are again substantial. For example, the coefficients in Column (1) imply that venture firms in the top quartile of internet exposure had a 47.5% larger decrease in fundraising hazard than those in the bottom quartile.

5.6 Companies Backed By Young VCs Late in Fundraising Cycle Were Most Affected

Thus, internet-focused venture firms faced increased difficulty in raising new funds after the collapse of the bubble. Also, at the same time, non-IT companies funded by these firms had increased difficulty in obtaining continuation financing in the post-bubble period. While these two facts would appear connected, little evidence has yet been presented to directly establish such a connection. If portfolio companies associated with more internet-focused venture firms were indeed less able to raise follow-on rounds due to the diminished fundraising capacity of their investors, one would expect the negative effect of investor internet exposure to be strongest for companies backed by firms that had not raised a new fund recently. This follows because such venture firms would be more likely to be running low on uninvested capital and, therefore, to be concerned about a decline in their fundraising capacity.

To test this, I re-estimate the specifications of Table 4b, now allowing all of the primary variables to interact with $YearsSinceRaised_{ijt}$, a variable representing the number of years since the venture firms backing the jth round of company i last raised a fund. In addition to these interactions, I also include an additional set of controls for $Post_t \times InternetExposure_{ij} \times Stage_{ij}$ and $InternetExposure_{ij} \times Stage_{ij}$ to ensure that terms involving $YearsSinceRaised_{ijt}$ do not also pick up effects from the stage of development of portfolio companies.[16]

Results are reported in Table 9. The primary coefficient of interest is that on the triple interaction term $Post_t \times InternetExposure_{ij} \times YearsSinceRaised_{ijt}$, which is estimated to be negative and statistically significant in Columns (3) through (6) and marginally significant in Columns (1) and (2). Overall, this suggests that the negative effect of the bubble's collapse on portfolio companies backed by high internet exposure firms was greater the longer it had been since those firms raised a new fund. Also, note that the estimated coefficient on the double interaction $Post_t \times InternetExposure_{ij}$ is not statistically significant. Therefore, it is not possible to reject the null that, for a company backed by a venture firm with a newly raised fund ($YearsSinceRaised_{ijt} = 0$), internet exposure was unrelated to the change in continuation hazard.

A venture firm's recent investment history would likely affect its fundraising less if the firm had a long previous investment track record. This would occur, for example, if limited partners updated their beliefs about a firm's investment ability in a Bayesian manner.[17]

[16] This may occur, for example, if low $YearsSinceRaised_{ijt}$ rounds tend to be in earlier-stage companies.

[17] Consistent with this, many well-established firms, including Kleiner Perkins, Charles River Ventures, and Accel Partners, returned capital to limited partners after the collapse, citing reduced investment opportunities. Such behavior would certainly seem to indicate that these firms were confident in their ability to raise future funds. Young venture firms, on the other hand, were likely less confident.

Thus, if companies backed by young firms were more affected by the internet exposure of their investors, this would provide further evidence that venture firm fundraising difficulties were indeed driving the baseline results. Indeed, the model presented earlier predicts that contagion should occur only if fundraising is sufficiently sensitive to performance, which would more likely be true for young venture firms.

I therefore re-estimate the specifications of the previous table, now allowing all the primary variables to further interact with $YoungVC_{ij}$, an indicator variable equaling one if the lead venture firm in the round was less than six years old at the peak of the bubble and zero otherwise. For expositional clarity, I present the results for the $YoungVC_{ij} = 1$ and $YoungVC_{ij} = 0$ subgroups separately, so as to avoid showing quadruple interaction terms.[18] Results are presented in Table 10. The primary coefficient of interest is again that on the triple interaction term $Post_t \times InternetExposure_{ij} \times YearsSinceRaised_{ijt}$. In the first three columns, this coefficient is estimated to be negative and statistically significant for the $YoungVC_{ij} = 1$ subgroup. In the final three columns, it is estimated to be smaller in magnitude and statistically insignificant for the $YoungVC_{ij} = 0$ subgroup. Most importantly, the difference in this coefficient for the two subgroups is large and statistically significant across all specifications. Therefore, to summarize, the portfolio companies that experienced the largest decline in continuation hazard when the technology bubble burst were those backed by venture firms that 1) had high internet exposure, 2) had not raised a fund recently, and 3) had a short previous investment track record. Again, these results are consistent with the venture firm fundraising mechanism.

[18]Note, however, that the region/stage/sector controls are in fact estimated using the whole sample.

5.7 Companies Backed by Internet VCs Were No Less Productive Prior to Collapse

Much of the discussion up to this point has implicitly assumed that non-IT companies funded by internet-focused venture firms were similar in quality to other non-IT companies. However, it is also possible that internet-focused venture firms tended to fund low-quality non-IT companies during the bubble and cut back funding to these companies subsequently. Note, the issue of quality is distinct from the endogeneity concerns discussed earlier. Again, due to the difference-in-differences framework used, the primary challenge to identification here comes not from unobservable differences in the *level* of company prospects, but rather unobservable differences in *changes* in company prospects coinciding with the end of the bubble. Thus, even if these companies tended to be of low quality, it might still be correct to say that the decline of the internet sector, coupled with the high exposure of their investors to that sector, *caused* them to lose access to capital. However, the welfare implications of that statement would change if these companies were negative NPV.[19] This might be the case if internet-focused venture firms anticipated high returns on their internet holdings and took chances on bad non-IT investments as a result. This would in some ways be akin to the agency costs of free cash flows (Jensen, 1986). On the other hand, one could also argue that the opposite might have been true. That is, venture firms with substantial internet holdings might have been more selective about making non-IT investments during the bubble period, as they might have perceived a larger opportunity cost in doing so.

To shed light on this issue, I examine whether companies with more internet-focused investors were less productive in terms of their patenting activity before the collapse of the

[19]This again parallels the internal capital market literature. While Lamont (1997) and others establish that diversified firms reallocate funds across divisions, it is not clear whether this is efficient. This question is taken up separately by e.g. Scharfstein (1998), Rajan, Servaes, and Zingales (2000), Whited (2001), and Chevalier (2004).

bubble. As discussed earlier, many of the companies in the sample operate in the biotechnology and medical/health sectors, where patents play a crucial role. I obtain patent data from the National Bureau of Economic Research (NBER) Patent Data Project (Hall, Jaffe, and Trajtenberg, 2001). These data are then matched with Thomson on company name, using the name standardization and matching procedures developed by the NBER Patent Data Project.[20] Matches are confirmed manually. I then limit the sample to companies that raised their first round of financing in the three years prior to the peak of the bubble (March 31, 1997, to March 31, 2000). For each company, I calculate the total number of successful patents applied for before the collapse. Also, for each of these patents, I calculate the total number of citations received during the three years following the date on which the patent was granted. Citations are a well-established proxy for the economic importance of a patent (Jaffe and Trajtenberg, 2002). As in Lerner, Sorensen, and Stromberg (2011), citations are counted for only a three-year window so that earlier patents do not have greater time to garner citations. Because both total patents and citations are count variables, I follow the literature and estimate negative binomial models of the form,

$$\lambda_i = exp(\beta_0 + \beta_1 InternetExposure_i + \boldsymbol{x}_{ijt}\boldsymbol{\beta}), \tag{5.3}$$

where λ_i is the intensity parameter. When total patents are the outcome of interest, i indexes portfolio companies; when citations are the outcome of interest, i indexes individual patents.

Results are reported in Table 11 with coefficients reported in terms of mean marginal effects to ease interpretation. In Columns (1) and (3), i indexes portfolio companies and λ_i represents company patenting intensity.[21] In both columns, the coefficient on $InternetExposure_i$

[20] See https://sites.google.com/site/patentdataproject/Home for the name-standardization programs and matching scripts used.

[21] In this analysis, companies differ in terms of their exposure time (the time they had available to apply for patents before the peak of the bubble) due to the fact that they were founded at different dates. This is adjusted for by altering the log likelihood function appropriately (Cameron and Trivedi, 1998), assuming

is estimated to be positive, but statistically insignificant. Thus, I fail to reject the null that the number of patents a company issued before the collapse of the bubble and the internet exposure of its investors were unrelated.

It is still possible that the ideas patented by non-IT companies backed by internet-focused firms tended to be less economically important. This is investigated in Columns (2) and (4), where λ_i represents patent citation intensity. It is well known that citation intensity varies widely across different patent classes and years. To account for this, I compute the baseline citation intensity γ_i as the mean number of citations received by all patents with the same class and grant year as patent i. [22] The variable $\ln(\gamma_i)$ is then included in the model with its coefficient constrained to one to convert citation intensity into relative terms, as in Lerner, Sorensen, and Stromberg (2011). In both Columns (2) and (4), the coefficient on $InternetExposure_i$ is again estimated to be positive and statistically insignificant. Thus, I also fail to reject the null that the number of citations a company's patents received and the internet exposure of its investors were unrelated. Therefore, while patenting productivity is by no means a perfect measure of company performance, there is no evidence from this standpoint to suggest that non-IT companies funded by more internet-focused firms tended to be of lower quality.

6 Conclusion

The structure of venture firms differs from that of other intermediaries in several ways, which ostensibly make them less fragile and more self-contained. In particular, limited partners are required to commit capital for the entire life of a fund; also, venture firms are typically limited in the extent to which they can invest in the same company out of multiple funds

exposure time to be the number of days between the first financing round and March 31, 2000.

[22] This includes patents outside of the sample. Citations for these patents are again counted for a three-year window after the date on which the patent was granted.

under their management. In this paper, I examine how this unique intermediation structure affects portfolio companies. In particular, I examine how venture-backed companies are affected when the prospects of others held in the same portfolio decline. I demonstrate in a simple model that it is ambiguous whether companies would be helped or hurt in this scenario. On the one hand, a company unrelated to the shock would become more attractive relative to other companies held in the same portfolio, making continuation financing easier to obtain. On the other hand, the company's financier may have diminished fundraising capacity as a result of the shock, making continuation financing more difficult to obtain.

To examine this topic empirically, I examine the effect of the collapse of the technology bubble on non-IT companies financed by venture firms that had high exposure to the internet sector. I estimate that the end of the bubble was associated with a substantially larger decline in continuation hazard for these non-IT portfolio companies as compared to others. Moreover, I provide evidence that this was not due to differences in the observable/unobservable characteristics of these companies. Indeed, for the same portfolio company receiving capital from multiple venture firms, investors with greater internet exposure were significantly less likely to continue participating in follow-on rounds. Exploring the mechanism underlying these results, I find that internet-focused venture firms suffered a larger decline in their fundraising capacity during this period, which may have been transmitted to their portfolio companies. Consistent with this, I also find that the negative effect of a venture firm's internet exposure on its portfolio companies was strongest for young venture firms, and for venture firms that had not raised a new fund recently. Finally, examining patenting productivity before the collapse of the bubble, I find no evidence that non-IT companies backed by internet-focused venture firms were of lower quality.

Overall, the results suggest that despite the fact that venture firms are structured to be more robust than most intermediaries, their portfolio companies can still face increased difficulty accessing capital when others that share the same investor suffer a negative shock. This can ultimately lead companies with high innovative potential to fail. More generally, knowing that contagion can occur even in the absence of maturity mismatch adds to our understanding of financial intermediation.

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Appendices

A Proofs

Proposition 1. *In the two-fund case without performance-sensitive fundraising, reverse contagion ($\frac{\partial x_{i1}}{\partial \theta_{j1}} < 0$) still occurs in the region of the parameter space in which the inequality constraint is non-binding; however, it is mitigated (the magnitude of $\frac{\partial x_{i1}}{\partial \theta_{j1}}$ is lower than in the one-fund case).*

Proof. The first part of the proposition is trivial given Equation 2.6. To see the second part, note that the inequality constraint is non-binding if and only if:

$$\begin{aligned} x_{i1} + x_{j1} &\leq F_I && \text{(A.1)} \\ \Leftrightarrow \frac{(F_I + F_{II})\theta_{i1}^2}{k^2 + \theta_{i1}^2 + \theta_{j1}^2} + \frac{(F_I + F_{II})\theta_{j1}^2}{k^2 + \theta_{i1}^2 + \theta_{j1}^2} &\leq F_I && \text{(A.2)} \\ \Leftrightarrow F_{II} &\leq \frac{F_I k^2}{\theta_{i1}^2 + \theta_{j1}^2}. && \text{(A.3)} \end{aligned}$$

In this region of the parameter space, investment in project i is less sensitive to the quality of project j in the two-fund case than in the one-fund case if and only if:

$$\begin{aligned} \frac{2(F_{II} + F_I)\theta_{i1}^2\theta_{j1}}{(k^2 + \theta_{i1}^2 + \theta_{j1}^2)^2} &< \frac{2F_I\theta_{i_1}^2\theta_{j_1}}{(\theta_{i1}^2 + \theta_{j1}^2)^2} && \text{(A.4)} \\ \Leftrightarrow \sqrt{\frac{F_I + F_{II}}{F_I}} &< \frac{k^2 + \theta_i^2 + \theta_j^2}{\theta_i^2 + \theta_j^2}. && \text{(A.5)} \end{aligned}$$

Given A.3, the expression on the left-hand side of A.5 is bounded above. Thus, it is sufficient to show that:

$$\begin{aligned} \sqrt{\frac{F_I + \frac{F_I k^2}{\theta_{i1}^2 + \theta_{j1}^2}}{F_I}} &< \frac{k^2 + \theta_i^2 + \theta_j^2}{\theta_i^2 + \theta_j^2} && \text{(A.6)} \\ \Leftrightarrow \sqrt{\frac{k^2 + \theta_i^2 + \theta_j^2}{\theta_i^2 + \theta_j^2}} &< \frac{k^2 + \theta_i^2 + \theta_j^2}{\theta_i^2 + \theta_j^2} && \text{(A.7)} \\ \Leftrightarrow 0 &< k^2 && \text{(A.8)} \end{aligned}$$

□

Proposition 2. *In the two-fund case with performance-sensitive fundraising, there exists b^* such that for $b > b^*$ ordinary contagion is present ($\frac{\partial x_{i1}}{\partial \theta_{j1}} > 0$) in the region of the parameter space in which the inequality constraint is non-binding.*

Proof. Now the inequality constraint is non-binding if and only if:

$$F_{II} \leq \frac{F_I k^2}{\theta_{i1}^2 + \theta_{j1}^2} \tag{A.9}$$

$$\Leftrightarrow b\frac{(\theta_{i1} + \theta_{j1})}{2} \leq \frac{F_I k^2}{\theta_{i1}^2 + \theta_{j1}^2} \tag{A.10}$$

$$\Leftrightarrow (\theta_{i1} + \theta_{j1})(\theta_{i1}^2 + \theta_{j1}^2) \leq \frac{2F_I k^2}{b} \tag{A.11}$$

$$\Rightarrow \theta_{i1} \leq (\frac{2F_I k^2}{b})^{\frac{1}{3}},\ \theta_{j1} \leq (\frac{2F_I k^2}{b})^{\frac{1}{3}}. \tag{A.12}$$

Ordinary contagion requires:

$$\frac{\partial x_{i1}}{\partial \theta_{j1}} > 0 \tag{A.13}$$

$$\Leftrightarrow \frac{\theta_{i1}^2[b(k^2 + \theta_{i1}^2 - 2\theta_{i1}\theta_{j1} - \theta_{j1}^2) - 4F_I\theta_{j1}]}{2(k^2 + \theta_{i1}^2 + \theta_{j1}^2)^2} > 0 \tag{A.14}$$

$$\Leftrightarrow b(k^2 + \theta_{i1}^2 - 2\theta_{i1}\theta_{j1} - \theta_{j1}^2) - 4F_I\theta_{j1} > 0. \tag{A.15}$$

Because θ_{i1} and θ_{j1} are bounded above as in A.12, the left-hand side of A.15 is bounded below by:

$$b(k^2 - 2(\frac{2F_I k^2}{b})^{\frac{2}{3}}) - 4F_I(\frac{2F_I k^2}{b})^{\frac{1}{3}}. \tag{A.16}$$

The limit of this expression as b goes to infinity is infinity. Therefore, by definition, there exists a b^* such that for all $b > b^*$, this expression is positive. $\square$

Figures

Figure 1
Timeline

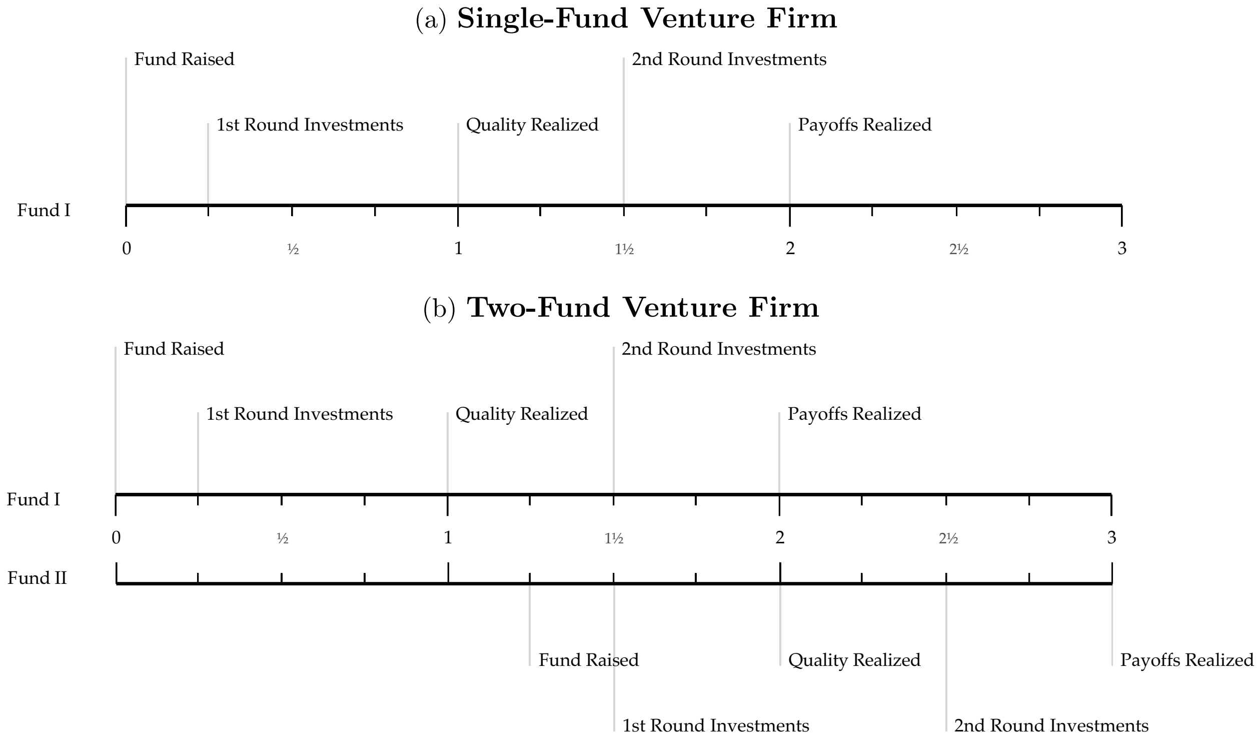


Figure 2

The Technology Bubble and Venture Capital

This figure shows buy-and-hold returns on publicly traded internet stocks alongside quarterly flows to venture capital funds. Internet stock returns are calculated as in Brunnermeier and Nagel (2004), using a value-weighted portfolio of stocks in the highest Nasdaq price/sales quintile, rebalanced monthly. Aggregate quarterly flows data are from Thomson. Flows in this case refers to commitments by limited partners to newly raised venture funds. Only U.S. based funds structured as independent private partnerships are included. Both total flows as well as flows to internet-specific funds (as categorized by Thomson) are shown. Flows are converted to real 2000 dollars using the GDP deflator. The vertical line corresponds to the peak of all three series and is located at March 31, 2000.

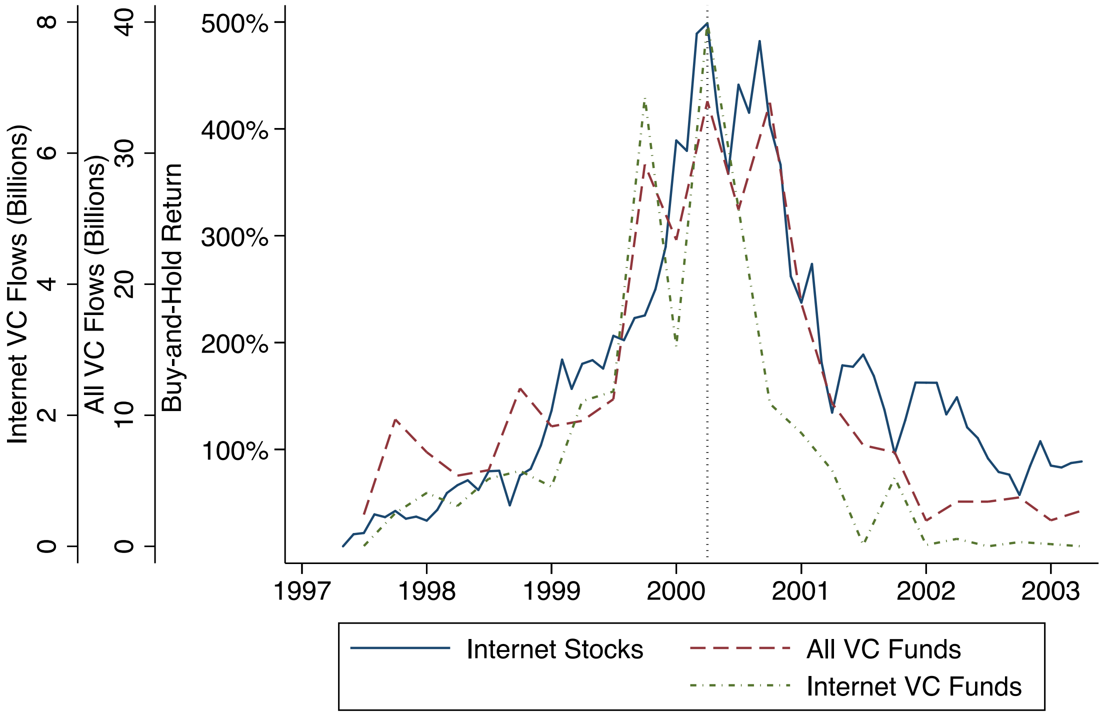
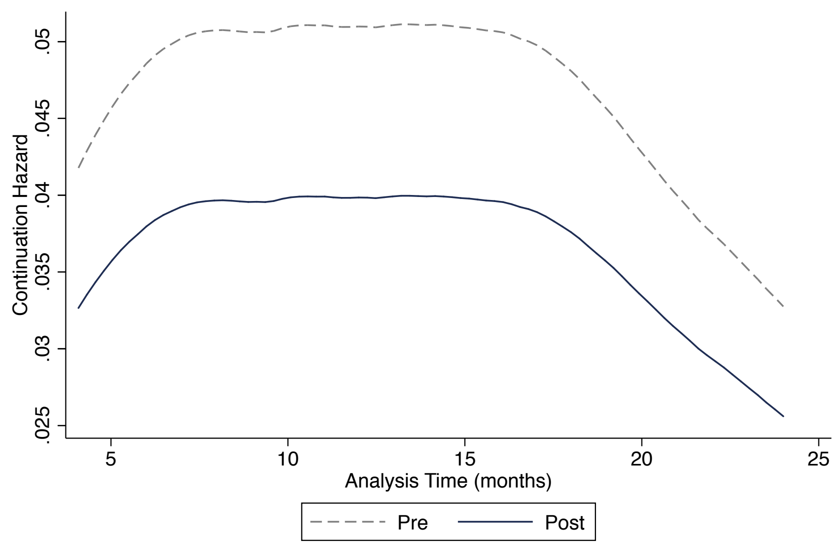


Figure 3
Smoothed Hazard Function

This figure depicts the results from Column (1) of Table 4a graphically using the hazard function. Hazard here refers to the hazard of a venture-backed company raising a follow-on round. Analysis time is the time elapsed since the previous round. A smoothed estimate of the baseline hazard function is backed out (given the estimated coefficients) using the Epanechnikov kernel with optimal bandwidth. The curves depicted reflect the baseline hazard shifted multiplicatively at various values of the covariates.

(a) **Internet VC**



(b) **Non-Internet VC**

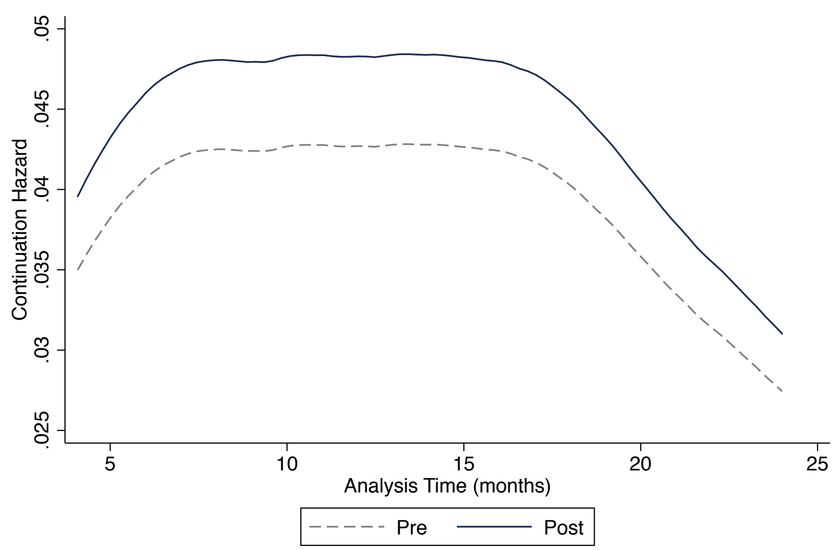
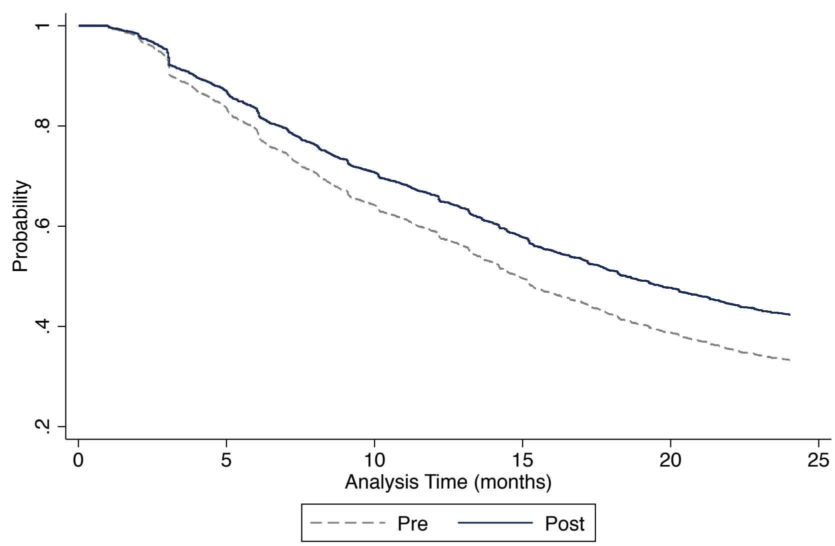


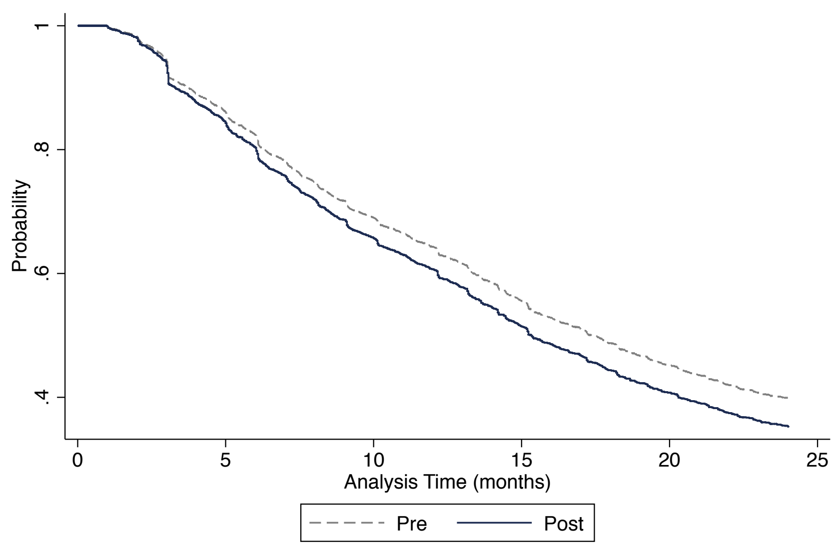
Figure 4
Survivor Function

This figure depicts the results from Column (1) of Table 4a graphically using the survivor function. In this case, a portfolio company is said to have "survived" until time τ if it had not raised another round of financing prior to that time. Analysis time is defined as the time elapsed since the previous financing round. The curves depicted reflect the baseline survivor function shifted by covariates, x, following the formula $S(\tau|x) = S_0(\tau)^{\exp(x\beta)}$.

(a) **Internet VC**



(b) **Non-Internet VC**



Tables

Table 1
Sample Composition

This table shows the composition of the sample by company region, sector, and stage of development. For region and sector, the sample composition is shown both at the financing round and company level. These differ as companies in the sample often raise multiple rounds of financing. In Panel (c), stage is broken down only by round because companies can be in different stages across rounds. In the final four columns, rounds back by syndicates in the bottom and top quartile of internet exposure are broken down separately.

	All				Non-Internet VC		Internet VC	
	Companies		Rounds		Rounds		Rounds	
	Freq	Pct	Freq	Pct	Freq	Pct	Freq	Pct
Panel A: Region								
Alaska/Hawaii	4	0.12	6	0.10	0	0.00	5	0.34
Great Lakes	199	6.16	334	5.50	105	6.77	68	4.62
Great Plains	165	5.11	284	4.68	86	5.54	68	4.62
Mid-Atlantic	142	4.40	276	4.55	63	4.06	65	4.42
N. California	486	15.05	1,013	16.69	146	9.41	320	21.74
NY Tri-State	394	12.20	693	11.42	225	14.50	162	11.01
New England	334	10.34	700	11.53	155	9.99	166	11.28
Northwest	106	3.28	213	3.51	60	3.87	44	2.99
Ohio Valley	246	7.62	437	7.20	104	6.70	153	10.39
Rocky Mountains	101	3.13	208	3.43	59	3.80	55	3.74
S. California	376	11.64	757	12.47	196	12.63	170	11.55
South	114	3.53	212	3.49	60	3.87	45	3.06
Southeast	303	9.38	509	8.39	129	8.31	94	6.39
Southwest	259	8.02	427	7.04	164	10.57	57	3.87
Total	3,229	100.00	6,069	100.00	1,552	100.00	1,472	100.00
Panel B: Sector								
Agr/Forestr/Fish	19	0.58	30	0.49	7	0.45	14	0.95
Biotechnology	483	14.80	1,044	17.10	287	18.41	192	13.00
Business Serv.	268	8.21	440	7.21	97	6.22	170	11.51
Construction	46	1.41	63	1.03	20	1.28	16	1.08
Consumer Related	593	18.17	988	16.19	219	14.05	308	20.85
Financial Services	227	6.96	333	5.46	88	5.64	111	7.52
Industrial/Energy	369	11.31	574	9.40	218	13.98	105	7.11
Manufact.	138	4.23	195	3.19	56	3.59	47	3.18
Medical/Health	959	29.39	2,217	36.32	501	32.14	456	30.87
Other	55	1.69	68	1.11	7	0.45	24	1.62
Transportation	87	2.67	130	2.13	46	2.95	32	2.17
Utilities	19	0.58	22	0.36	13	0.83	2	0.14
Total	3,263	100.00	6,104	100.00	1,559	100.00	1,477	100.00
Panel C: Stage								
Early Stage	-	-	1,484	24.31	367	23.54	405	27.42
Expansion	-	-	3,100	50.79	821	52.66	710	48.07
Later Stage	-	-	790	12.94	168	10.78	178	12.05
Startup/Seed	-	-	730	11.96	203	13.02	184	12.46

Total	-	-	6,104	100.00	1,559	100.00	1,477	100.00

Table 2
Summary Statistics

This table shows summary statistics for the key variables used in the analysis. The sample is restricted to financing rounds of venture-backed non-IT portfolio companies based in the U.S. The sample period is from March 31, 1997, to March 31, 2003. Each variable is shown at the level of observation at which it varies. The degree of a venture capital firm k's exposure to internet investments, $InternetExposure_k$, is measured as the percentage of the total amount invested by the firm that was disbursed to companies operating in the internet sector during the 10 years leading up to the peak of the bubble (March 31, 2000). Internet exposure for the syndicate backing the jth round of company i is then calculated as 1) the mean of $InternetExposure_k$ for each firm k participating in the round (weighted by round contributions) and 2) the $InternetExposure_k$ of the lead venture firm in the round, where the lead is defined as the firm that has invested in the company the longest (ties are broken by cumulative disbursements to the company inclusive of the current round). The number of investors refers to the number of venture firms participating in the round. At the venture firm level, the number of investments refers to the number of company-rounds the venture firms participated in during the 10 years leading up to the peak of the bubble. Firm age refers to the age of the venture firm at the peak of the bubble in years. At the quarter level, internet VC flows and total VC flows are defined as in Figure 2. Venture firm dropout is defined at the company-round-VC level. For each continuation round raised by a company, there is an observation for each venture firm that participated in the previous round. If the venture firm participated in the current round, $VCDropout_{ijkt}$ equals zero; otherwise, if the venture firm did not participate, $VCDropout_{ijkt}$ is equal to one. One exception to this rule is made if the venture firm is observed participating again in subsequent rounds of the company. Then, the firm is considered a participant in the current round as its omission is taken to be a data error. At the company level, total patents refers to the number of patents a portfolio company successfully applied for before the peak of the bubble. At the patent level, number of citations refers to the number of citations the patent received in the first three years after being granted.

	p25	p50	p75	Mean	s.d.	N
Round Level						
Internet Exposure (Whole Syndicate)	0.0735	0.173	0.270	0.192	0.154	5908
Internet Exposure (Lead VC)	0.0512	0.163	0.275	0.187	0.164	5330
Number of Investors	1	2	4	2.935	2.461	6104
VC Level						
Internet Exposure	0.0330	0.193	0.383	0.244	0.235	782
Number of Investments	11	25.50	62	59.42	100.0	782
Firm Age	2.836	9.292	16.54	10.59	8.915	596
Quarter Level						
Internet VC Flows (Billions)	0.0596	0.980	2.206	1.638	2.171	24
Total VC Flows (Billions)	3.924	8.433	15.29	11.73	10.11	24
Round-VC Level						
Firm Dropout	0	0	0	0.116	0.321	10427
Company Level						
Total Patents (1997Q2-2000Q2)	0	2	4	3.822	10.92	444
Patent Level						
Number of Citations (First Three Years)	1	4	10	8.607	12.69	1683

Table 3

On Average, IT Companies Affected, Non-IT Companies Unaffected

This table shows the results of estimating univariate Cox proportional hazard models of the form

$$h_{ijt}(\tau) = h_0(\tau)\exp(\beta_1 Post_t),$$

for rounds in each IT and non-IT sector in the data. Analysis time τ is defined as the time since company i raised its jth round. The variable $Post_t$ is an indicator equaling one if the date is after the peak of the technology bubble (March 31, 2000) and zero otherwise. Note $Post_t$ is a time-varying covariate, i.e. it can change in the middle of a spell. The sample is restricted to financing rounds of venture-backed U.S. companies. The sample period is from March 31, 1997, to March 31, 2003. Raw coefficients are reported. Standard errors are in brackets and are clustered by portfolio company. * and ** denote statistical significance at the 10% and 5% level, respectively.

(a) **IT Sectors**

	Communications	Hardware	Software	Internet	Semiconductors
Post	-0.254^{**}	-0.259^{**}	-0.314^{**}	-0.743^{**}	-0.107
	[0.0479]	[0.0842]	[0.0328]	[0.0300]	[0.0657]
$\exp(\beta_1)-1$	-0.224	-0.228	-0.269	-0.524	-0.102
Spells	3,653	1,091	7,476	8,871	1,965

(b) **Non-IT Sectors**

	Biotech	Consumer	Energy	Medical	Other Non-IT
Post	-0.0938	-0.0897	0.0860	-0.0928^{*}	-0.0614
	[0.0658]	[0.0862]	[0.117]	[0.0475]	[0.0789]
$\exp(\beta_1)-1$	-0.0895	-0.0858	0.0898	-0.0887	-0.0596
Spells	1,680	1,804	1,156	3,320	2,504

Table 4

Non-IT Companies Backed by Internet VCs Were Affected

This table shows the results of estimating Cox proportional hazard models. Analysis time, τ, is defined as the time since company i raised its jth round of financing, and the event of interest is the raising of a $(j+1)th$ round. The variable $Post_t$ is an indicator equaling one if the date, t, is after the peak of the technology bubble (March 31, 2000) and zero otherwise. Note $Post_t$ is a time-varying covariate, i.e. it can change in the middle of a spell. The degree of a syndicate's exposure to internet investments, $InternetExposure_{ij}$, is measured as in Table 2. Based on these measures, the indicator variable $InternetVC_{ij}$ is set equal to one if the syndicate backing the round is in the top quartile of $InternetExposure_{ij}$ and zero if it is in the bottom quartile. The middle two quartiles are dropped from this analysis in Panel (a). In Panel (c), the variable $\log(InternetFlows_t)$ represents the log of quarterly aggregate flows into (U.S. based, independent, private) internet-specific venture funds, from Thomson. Flows are converted to 2000 dollars using the GDP deflator. When company controls are included, the most prevalent categories (Northern California, expansion, and medical/health) are omitted. The sample is restricted to financing rounds of venture-backed non-IT portfolio companies based in the U.S. The sample period is from March 31, 1997, to March 31, 2003. Raw coefficients are reported. Standard errors are in brackets and are clustered by portfolio company in the first three columns as well as lead venture firm in the final three columns, as in Cameron, Gelbach, and Miller (2011). * and ** denote statistical significance at the 10% and 5% level, respectively.

(a) **Discrete Treatment, Pre/Post, Extreme Quartiles**

	Whole Syndicate			Lead VC		
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.123	0.0772	−0.0112	0.0978	0.0442	0.0425
	[0.0759]	[0.0764]	[0.162]	[0.0794]	[0.0762]	[0.186]
Internet VC	0.178**	0.156**	0.149*	0.139	0.122	0.109
	[0.0793]	[0.0790]	[0.0788]	[0.115]	[0.0962]	[0.0950]
Post × Internet VC	−0.370**	−0.290**	−0.260**	−0.393**	−0.317**	−0.295**
	[0.104]	[0.106]	[0.106]	[0.117]	[0.112]	[0.113]
Region FE	No	Yes	Yes	No	Yes	Yes
Sector FE	No	Yes	Yes	No	Yes	Yes
Stage FE	No	Yes	Yes	No	Yes	Yes
Post × Region FE	No	No	Yes	No	No	Yes
Post × Sector FE	No	No	Yes	No	No	Yes
Post × Stage FE	No	No	Yes	No	No	Yes
$\exp(\beta_3)-1$	−0.309	−0.252	−0.229	−0.325	−0.271	−0.255
Spells	3,036	3,024	3,024	2,687	2,671	2,671

Table 4
(continued)

(b) **Continuous Treatment, Pre/Post, Whole Sample**

	Whole Syndicate			Lead VC		
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.0721	0.0579	0.105	0.111*	0.0803	0.191
	[0.0600]	[0.0624]	[0.117]	[0.0615]	[0.0631]	[0.134]
Internet Exposure	0.512**	0.541**	0.519**	0.359	0.329	0.343
	[0.188]	[0.196]	[0.194]	[0.254]	[0.244]	[0.242]
Post × Internet Exposure	−0.996**	−0.848**	−0.792**	−0.906**	−0.726**	−0.753**
	[0.244]	[0.256]	[0.256]	[0.271]	[0.280]	[0.280]
Region FE	No	Yes	Yes	No	Yes	Yes
Sector FE	No	Yes	Yes	No	Yes	Yes
Stage FE	No	Yes	Yes	No	Yes	Yes
Post × Region FE	No	No	Yes	No	No	Yes
Post × Sector FE	No	No	Yes	No	No	Yes
Post × Stage FE	No	No	Yes	No	No	Yes
Spells	5,908	5,889	5,889	5,330	5,296	5,296

(c) **Continuous Treatment, Quarterly Internet Flows, Whole Sample**

	Whole Syndicate			Lead VC		
	(1)	(2)	(3)	(4)	(5)	(6)
log(Internet Flows)	0.0167	0.0153	0.00760	0.0123	0.0124	−0.0103
	[0.0183]	[0.0195]	[0.0271]	[0.0230]	[0.0238]	[0.0267]
Internet Exposure	0.00147	0.121	0.111	−0.0745	−0.0000116	0.00549
	[0.163]	[0.156]	[0.155]	[0.202]	[0.179]	[0.178]
log(Internet Flows) × Internet Exposure	0.162**	0.166**	0.144**	0.183**	0.180**	0.175**
	[0.0554]	[0.0539]	[0.0512]	[0.0679]	[0.0683]	[0.0619]
Region FE	No	Yes	Yes	No	Yes	Yes
Sector FE	No	Yes	Yes	No	Yes	Yes
Stage FE	No	Yes	Yes	No	Yes	Yes
log(Internet Flows) × Region FE	No	No	Yes	No	No	Yes
log(Internet Flows) × Sector FE	No	No	Yes	No	No	Yes
log(Internet Flows) × Stage FE	No	No	Yes	No	No	Yes
Spells	5,908	5,889	5,889	5,330	5,296	5,296

Table 5
Additional Robustness Tests

This table shows the results of estimating Cox proportional hazard models of the form

$$h_{ijt}(\tau) = h_0(\tau)exp(\beta_1 Post_t + \beta_2 InternetExposure_{ij} + \beta_3 Post_t \times InternetExposure_{ij} + \boldsymbol{x}_{ijt}\boldsymbol{\beta}).$$

Variables are defined as in Table 4b. The sample is restricted to financing rounds of venture-backed non-IT portfolio companies based in the U.S. The sample period is from March 31, 1997, to March 31, 2003. In Column (1) consumer-related non-IT companies are excluded from the sample. In Column (2) non-IT companies categorized as producing "Other Products" are excluded from the sample. In Column (3) non-IT companies with the words "Internet," "Online," "Web," "E-Commerce," "Software," "Digital," "Electronic," "Computer," "E-mail," "Hardware," or "Network" in the detailed business description, product keywords, or technology description are excluded. In Column (4) companies that are categorized by VentureSource as IT are excluded. Raw coefficients are reported. Standard errors are in brackets and are clustered by portfolio company in the first three columns as well as lead venture firm in the final three columns, as in Cameron, Gelbach, and Miller (2011). * and ** denote statistical significance at the 10% and 5% level, respectively.

	Lead VC			
	(1) Ex. Consumer-Related	(2) Ex. Other Non-IT	(3) Ex. Tech Description	(4) Ex. VentureSource IT
Post	0.129	0.194	0.158	0.203
	[0.142]	[0.134]	[0.137]	[0.135]
Internet Exposure	0.208	0.206	0.247	0.358
	[0.255]	[0.264]	[0.258]	[0.245]
Post × Internet Exposure	−0.605**	−0.730**	−0.630**	−0.757**
	[0.303]	[0.303]	[0.302]	[0.283]
Region FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes
Post × Region FE	Yes	Yes	Yes	Yes
Post × Sector FE	Yes	Yes	Yes	Yes
Post × Stage FE	Yes	Yes	Yes	Yes
Spells	4,413	4,187	4,665	5,198

Table 6

Continuation Hazard Did Not Increase as Bubble Inflated, Decreased as Deflated

This table shows the results of estimating Cox proportional hazard models of the form

$$h_{ijt}(\tau) = h_0(\tau)exp(\beta_1 \log(InternetFlows_t) + \beta_2 InternetExposure_{ij} + \beta_3 \log(InternetFlows_t) \times InternetExposure_{ij} + \beta_4 \log(InternetFlows_t) \times InternetExposure_{ij} \times Post_t + \boldsymbol{x}_{ijt}\boldsymbol{\beta}).$$

Analysis time, τ, is defined as the time since company i raised its jth round. The variable $\log(InternetFlows_t)$ represents the log of quarterly aggregate flows into (U.S. based, independent, private) internet-specific venture funds, from Thomson. All other variables are defined as in Table 4. When company controls are included, the most prevalent categories (Northern California, expansion, and medical/health) are omitted. The sample is restricted to financing rounds of venture-backed non-IT portfolio companies based in the U.S. The sample period is from March 31, 1997, to March 31, 2003. Raw coefficients are reported. Standard errors are in brackets and are clustered by portfolio company and quarter in the first three columns as well as lead venture firm in the final three columns, as in Cameron, Gelbach, and Miller (2011). * and ** denote statistical significance at the 10% and 5% level, respectively.

	Whole Syndicate			Lead VC		
	(1)	(2)	(3)	(4)	(5)	(6)
log(Internet Flows)	0.0199	0.0186	0.00894	0.0156	0.0158	−0.00925
	[0.0173]	[0.0185]	[0.0269]	[0.0225]	[0.0232]	[0.0269]
Internet Exposure	0.0266	0.148	0.137	−0.0500	0.0253	0.0317
	[0.170]	[0.165]	[0.163]	[0.204]	[0.184]	[0.184]
log(Internet Flows) × Internet Exposure	−0.0555	−0.0581	−0.0793	−0.0693	−0.0792	−0.0880
	[0.0930]	[0.0896]	[0.0856]	[0.105]	[0.105]	[0.100]
log(Internet Flows) × Internet Exposure ×	0.287**	0.299**	0.297**	0.340**	0.352**	0.354**
Post	[0.106]	[0.101]	[0.0984]	[0.109]	[0.104]	[0.102]
Region FE	No	Yes	Yes	No	Yes	Yes
Sector FE	No	Yes	Yes	No	Yes	Yes
Stage FE	No	Yes	Yes	No	Yes	Yes
log(Internet Flows) × Region FE	No	No	Yes	No	No	Yes
log(Internet Flows) × Sector FE	No	No	Yes	No	No	Yes
log(Internet Flows) × Stage FE	No	No	Yes	No	No	Yes
Spells	5,908	5,889	5,889	5,330	5,296	5,296

Table 7

For Same Company, Internet VCs Became More Likely to Drop Out of Rounds

This table shows the results of estimating models of the form

$$VCDropout_{ijkt} = \alpha_i + \beta_1 Post_t + \beta_2 InternetExposure_k + \beta_3 Post_t \times InternetExposure_k + \boldsymbol{x}_{ijt}\boldsymbol{\beta}.$$

Observations are at the company-round-VC level. For each continuation round raised by a company, there is an observation for each venture firm that participated in the previous round. If the venture firm participated in the current round, $VCDropout_{ijkt}$ equals zero; otherwise, if the venture firm did not participate, $VCDropout_{ijkt}$ is equal to one. One exception to this rule is made if the venture firm is observed participating again in subsequent rounds of the company. Then, the firm is considered a participant in the current round, as its omission is taken to be a data error. All other variables are defined as in Table 4. When company controls are included, the most prevalent categories (Northern California, expansion, and medical/health) are omitted. The sample is restricted to financing rounds of ventured-backed non-IT portfolio companies based in the U.S. The sample period is from March 31, 1997, to March 31, 2003. Standard errors are in brackets and are clustered by company and venture firm in all specifications, as in Cameron, Gelbach, and Miller (2011). * and ** denote statistical significance at the 10% and 5% level, respectively.

	OLS		Company FE	
	(1)	(2)	(3)	(4)
Internet Exposure	−0.00316	−0.0320	−0.00743	−0.0181
	[0.0628]	[0.0599]	[0.0622]	[0.0623]
Post	−0.0169	−0.0992**	0.139**	0.113**
	[0.0203]	[0.0334]	[0.0218]	[0.0265]
Post × Internet Exposure	0.186**	0.222**	0.171**	0.177**
	[0.0821]	[0.0839]	[0.0818]	[0.0818]
Company FE	No	No	Yes	Yes
Region FE	No	Yes	No	No
Sector FE	No	Yes	No	No
Stage FE	No	Yes	No	Yes
Post × Region FE	No	Yes	No	No
Post × Sector FE	No	Yes	No	No
Post × Stage FE	No	Yes	No	Yes
Observations	6,508	6,508	6,508	6,508

Table 8

Internet VCs Had Increased Fundraising Difficulty after Collapse

Each column of this table reports the results of re-estimating the Cox proportional hazards models of Table 4 at the venture firm level. Specifically, rather than estimating the hazard of a portfolio company raising a continuation round from venture firms, the hazard of a venture firm raising a follow-on fund from limited partners is now estimated. Analysis time, τ, is defined as the time since venture firm k raised its last fund. The sample period is from March 31, 1997, to March 31, 2003. Raw coefficients are reported. Standard errors are in brackets and are clustered by venture firm and also by quarter in the third column, as in Cameron, Gelbach, and Miller (2011). * and ** denote statistical significance at the 10% and 5% level, respectively.

	(1)	(2)	(3)
Post	0.0445	-0.182^{*}	
	[0.143]	[0.0960]	
Internet VC	0.438^{**}		
	[0.184]		
Post × Internet VC	-0.645^{**}		
	[0.188]		
Internet Exposure		0.534^{**}	0.0182
		[0.205]	[0.221]
Post × Internet Exposure		-0.875^{**}	
		[0.259]	
log(Internet Flows)			0.200^{**}
			[0.0692]
log(Internet Flows) × Internet Exposure			0.321^{**}
			[0.102]
Spells	716	1,428	1,428

Table 9
Companies Backed by VCs Late in Fundraising Cycle Were Most Affected

This table shows the results of estimating Cox proportional hazards models of the form

$$h_{ijt}(\tau) = h_0(\tau)exp(\beta_1 Post_t + \beta_2 InternetExposure_{ij} + \beta_3 YearsSinceRaised_{ijt} + \beta_4 Post_t \times InternetExposure_{ij} + \beta_5 Post_t \times YearsSinceRaised_{ijt} + \beta_6 InternetExposure_{ij} \times YearsSinceRaised_{ijt} + \beta_7 Post_t \times InternetExposure_{ij} \times YearsSinceRaised_{ijt} + \boldsymbol{x}_{ijt}\boldsymbol{\beta}).$$

The variable $YearsSinceRaised_{kt}$ represents the number of years—as of time t—since firm k last raised a new fund from limited partners. This is aggregated for a syndicate in the same two ways as $InternetExposure_k$. All other variables are defined as in Table 4. When company controls are included, the most prevalent categories (Northern California, expansion, and medical/health) are omitted. The sample is restricted to financing rounds of venture-backed U.S. companies operating in non-IT sectors. The sample period is from March 31, 1997, to March 31, 2003. Raw coefficients are reported. Standard errors are in brackets and are clustered by portfolio company in the first three columns, as well as lead venture firm in the final three columns, as in Cameron, Gelbach, and Miller (2011). * and ** denote statistical significance at the 10% and 5% level, respectively.

	Whole Syndicate			Lead VC		
	(1)	(2)	(3)	(4)	(5)	(6)
Post	−0.0248	−0.0589	−0.145	0.0370	0.00663	0.0562
	[0.0978]	[0.0986]	[0.153]	[0.0960]	[0.0949]	[0.155]
Internet Exposure	−0.0489	0.179	−0.241	−0.0335	0.217	0.0288
	[0.289]	[0.292]	[0.393]	[0.360]	[0.341]	[0.439]
Years Since Raised	−0.0605**	−0.0407**	−0.0440**	−0.0386	−0.0163	−0.0152
	[0.0203]	[0.0206]	[0.0212]	[0.0247]	[0.0228]	[0.0231]
Post × Internet Exposure	−0.436	−0.228	0.267	−0.334	−0.0994	0.0646
	[0.416]	[0.416]	[0.524]	[0.420]	[0.416]	[0.508]
Post × Years Since Raised	0.0187	0.0312	0.0435	0.0258	0.0367	0.0419
	[0.0365]	[0.0367]	[0.0378]	[0.0346]	[0.0340]	[0.0348]
Internet Exposure × Years Since Raised	0.0964	0.0509	0.0621	0.0914	0.0457	0.0276
	[0.0890]	[0.0907]	[0.0913]	[0.120]	[0.115]	[0.114]
Post × Internet Exposure ×	−0.309*	−0.348*	−0.358**	−0.466**	−0.533**	−0.513**
Years Since Raised	[0.177]	[0.178]	[0.180]	[0.199]	[0.198]	[0.200]
Region FE	No	Yes	Yes	No	Yes	Yes
Stage FE	No	Yes	Yes	No	Yes	Yes
Sector FE	No	Yes	Yes	No	Yes	Yes
Post × Region FE	No	No	Yes	No	No	Yes
Post × Sector FE	No	No	Yes	No	No	Yes
Post × Stage FE	No	No	Yes	No	No	Yes
Internet Exposure × Stage FE	No	No	Yes	No	No	Yes
Post × Internet Exposure × Stage FE	No	No	Yes	No	No	Yes
Spells	5,103	5,088	5,088	4,397	4,372	4,372

Table 10

Companies Backed by VCs Late in Fundraising Cycle Were Most Affected: Young vs. Old VCs

This table shows the results of estimating Cox proportional hazards models of the form

$$h_{ijt}(\tau) = h_0(\tau)exp(\beta_1 Post_t + \beta_2 InternetExposure_{ij} + \beta_3 YearsSinceRaised_{ijt} + \beta_4 Post_t \times InternetExposure_{ij} + \beta_5 Post_t \times YearsSinceRaised_{ijt} + \beta_6 InternetExposure_{ij} \times YearsSinceRaised_{ijt} + \beta_7 Post_t \times InternetExposure_{ij} \times YearsSinceRaised_{ijt} + \boldsymbol{x}_{ijt}\boldsymbol{\beta}).$$

Variables are defined as in Table 9. The first three columns show results for rounds backed by lead venture firms less than six years old at the peak. The final three columns show results for rounds backed by lead venture firms greater than six years old at the peak. Region/stage/sector controls are estimated based on the whole sample in all specifications. The sample is restricted to financing rounds of venture-backed U.S. companies operating in non-IT sectors. The sample period is from March 31, 1997, to March 31, 2003. Raw coefficients are reported. Standard errors are in brackets and are clustered by portfolio company as well as lead venture firm, as in Cameron, Gelbach, and Miller (2011). * and ** denote statistical significance at the 10% and 5% level, respectively.

	Lead VC Age < 6 Years			Lead VC Age ≥ 6 Years		
	(1)	(2)	(3)	(4)	(5)	(6)
Post	−0.295	−0.222	−0.244	0.141	0.0912	0.124
	[0.215]	[0.211]	[0.250]	[0.118]	[0.113]	[0.171]
Internet Exposure	−0.622	−0.0628	−0.488	−0.212	−0.00478	−0.0876
	[0.654]	[0.654]	[0.725]	[0.458]	[0.409]	[0.518]
Years Since Raised	−0.142	−0.0595	−0.0797	−0.0361	−0.0164	−0.0125
	[0.128]	[0.131]	[0.131]	[0.0259]	[0.0238]	[0.0242]
Post × Internet Exposure	0.982	0.921	1.350*	−0.908	−0.614	−0.481
	[0.696]	[0.702]	[0.803]	[0.574]	[0.557]	[0.627]
Post × Years Since Raised	0.177	0.123	0.150	−0.00807	0.00752	0.0104
	[0.132]	[0.136]	[0.134]	[0.0409]	[0.0411]	[0.0422]
Internet Exposure × Years Since Raised	0.623	0.410	0.528	0.0664	0.0321	−0.00477
	[0.417]	[0.440]	[0.444]	[0.134]	[0.127]	[0.127]
Post × Internet Exposure ×	−1.368**	−1.260**	−1.398**	−0.190	−0.265	−0.227
Years Since Raised	[0.480]	[0.497]	[0.505]	[0.226]	[0.233]	[0.234]
Region FE	No	Yes	Yes	No	Yes	Yes
Stage FE	No	Yes	Yes	No	Yes	Yes
Sector FE	No	Yes	Yes	No	Yes	Yes
Post × Region FE	No	No	Yes	No	No	Yes
Post × Sector FE	No	No	Yes	No	No	Yes
Post × Stage FE	No	No	Yes	No	No	Yes
Internet Exposure × Stage FE	No	No	Yes	No	No	Yes
Post × Internet Exposure × Stage FE	No	No	Yes	No	No	Yes
Spells	1,034	1,030	1,030	3,341	3,320	3,320

Table 11

Companies Backed by Internet VCs Were No Less Productive Prior to Collapse

This table shows the results of estimating equations of the form

$$\lambda_i = \exp(\beta_0 + \beta_1 InternetExposure_i + \boldsymbol{x}_{ijt}\boldsymbol{\beta})$$

where λ is the intensity parameter of the negative binomial distribution. In Columns (1) and (3), i indexes venture-backed portfolio companies, and λ_i represents patenting intensity before March 31, 2000. Companies differ in terms of their exposure time due to the fact that they received their first financing round at different dates. This is adjusted for by altering the log likelihood function appropriately (Cameron and Trivedi, 1998). In Columns (2) and (4), i indexes individual patents, and λ_i represents citation intensity. All patents have the same exposure time in this case, as only citations that occurred in the three years following the date on which a patent was granted are counted. Also, in Columns (2) and (4), $\ln(\gamma_i)$ is included as a dependent variable with its coefficient constrained to equal one, as in Lerner, Sorensen, and Stromberg (2011). The variable γ_i represents the mean number of citations received (in the first three years) for all patents with the same USPTO patent class and grant year as patent i. This procedure takes into account the fact that patents with different classes and grant years differ in terms of their baseline citation intensity. The variable $InternetExposure_i$ represents the internet exposure of the syndicate backing the first round of company i, as defined in Table 4. The sample is limited to non-IT companies that raised their first round between March 31, 1997, and March 31, 2000. Only patents applied for between these dates are included as well. Coefficients are presented in terms of mean marginal effects. Standard errors are in brackets and are clustered by portfolio company in Column (2), as well as by lead venture firm in Column (4), as in Cameron, Gelbach, and Miller (2011). * and ** denote statistical significance at the 10% and 5% level, respectively.

	Whole Syndicate		Lead VC	
	(1)	(2)	(3)	(4)
	Total Patents	Relative Citations	Total Patents	Relative Citations
Internet Exposure	1.890	2.497	0.458	0.973
	[2.215]	[3.664]	[2.541]	[3.360]
Region FE	Yes	No	Yes	No
Sector FE	Yes	No	Yes	No
Observations	443	1,574	419	1,456