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Propagation of Financial Shocks: The Case of Venture Capital

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This paper investigates how venture-backed companies are affected when others sharing the same investor suffer a negative shock. In theory, companies may be helped or hurt in this scenario. To examine the topic empirically, I estimate the impact of the collapse of the technology bubble on non-information-technology (non-IT) companies that were held alongside IInternet companies in venture portfolios. Using a difference-in-differences framework, I find that the end of the bubble was associated with a significantly larger decline in the probability of raising continuation financing for these non-IT companies in comparison to others. This does not appear to be driven by unobservable company characteristics such as company quality or IT relatedness; for the same portfolio company receiving capital from multiple venture firms, investors with greater Internet exposure were significantly less likely to continue to participate in follow-on rounds.

Keywords: intermediation; contagion; venture capital; technology bubble; Internet; lock-in
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1. Introduction

Venture capitalists typically invest in a portfolio of companies; however, little is known about the way in which these investments interact. In particular, it is possible that there may be spillovers across portfolio companies. That is, a company's ability to obtain further resources and ultimately succeed may be affected by being held in the same portfolio as others that have experienced a shock to their prospects. In theory, if the resources available to the companies in a portfolio remain relatively fixed after some experience a negative shock, the shock may help unrelated companies. These companies become more attractive in relative terms. On the other hand, if the resources available to the companies in a portfolio decline after some suffer a negative shock, the shock may hurt unrelated companies. In this case, the increase in their relative attractiveness could be outweighed by the decrease in resources available to them. Finally, if companies can easily switch investors, companies unrelated to the shock may be unaffected, regardless of their portfolio peers. This paper attempts to shed light on whether companies in a venture portfolio do indeed become artificially linked as a result of sharing a common investor.

In the context of venture capital, it is plausible that the resources available to the companies in a portfolio remain relatively fixed after some experience a negative shock. After a fund is raised, the extent to which it can grow or shrink is limited; funds are typically close ended, and investors are required to commit capital for the entire life of a fund. Funds are also somewhat self-contained in the sense that partnership agreements often limit the extent to which the same company can be financed out of multiple funds under the management of the same venture firm. Finally, funds also have fairly fixed human capital resources due to covenants that restrict their ability to add or remove general partners. All of this is in stark contrast to the structure of banks and other financial intermediaries.

However, there are mechanisms through which the resources available to the companies in a venture portfolio may decline after some experience a negative shock. First, if a venture firm holds a portfolio with high exposure to the shock, it will likely have fewer companies that have an early IPO or acquisition. This means there will be more companies competing for resources from that venture firm and thus fewer resources available per company. There also may be fewer resources available in total, because a venture firm with fewer early exits would have less capital to recycle and also may have greater difficulty attracting syndication partners. Further, it is possible that even if total resources or resources per company remain unchanged, the resources available to companies unrelated to the shock decrease, as those affected by the shock require more funding and operational support as a result. Perhaps most importantly, if a venture firm holds a portfolio with high exposure to the shock, it will likely have increased difficulty raising a new fund. This means that new companies that would otherwise have been funded out of a new fund may have to be funded out of the existing fund instead, decreasing the resources available to existing portfolio companies further.

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 et al. 2009, Hochberg and Westerfield 2012). 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 semiparametric 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 significantly larger decline in continuation hazard with the collapse of the bubble than did those in the control group. In particular, an increase of one standard deviation in VC Internet exposure is associated with a 15.3% larger decline in the (instantaneous) probability of raising a follow-on round.

The primary concern with this identification strategy is that companies backed by more Internet-exposed 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, because these were less likely to be related to Internet technologies, regardless of investor Internet exposure. However, although 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-exposed 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 because of such observable characteristics, I control for heterogeneous time trends based on these characteristics. Controlling for these trends 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 (2012). 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 to participate 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, an increase of one standard deviation in Internet exposure was associated with an additional 13% decrease in fund-raising hazard when the bubble burst.

A venture firm that had not recently raised a new fund from limited partners would likely be more concerned about a decline in its fund-raising capacity (due to Internet exposure) than a firm that had 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 fund-raising 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-exposed 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 before 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, because of 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-exposed 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.

Overall, these findings have important implications for both entrepreneurs and venture capitalists. For entrepreneurs, they suggest that many factors must be considered when choosing a venture capitalist: not only is it important to consider an investor's ability to add value through operational support and governance, it is also important to consider the investor's other portfolio companies and how they may impact follow-on financing. This increases the need for reverse due diligence. For venture capitalists, the findings suggest that each investment comes with a potential externality in the sense that negative shocks to certain portfolio companies may cause subsequent underinvestment in others. This makes the venture capitalist's portfolio problem more complicated.

This paper relates to several distinct lines of research. Many papers have found that, among financial intermediaries, venture capitalists play an unusually active role in their portfolio companies by sitting on boards, shaping senior management, providing access to key resources, and aiding in company professionalization in myriad other ways (Lerner 1995; Hellmann and Puri 2000, 2002; Baker and Gompers 2003; Kaplan and Strömberg 2004). In fact, entrepreneurs accept lower valuations in order to be affiliated with venture firms with a reputation for providing these services well (Hsu 2004). As pointed out by Admati and Pfleiderer (1994), the close involvement of venture capitalists makes their portfolio companies susceptible to informational lock-in. Indeed, there is much evidence that it is difficult to switch VCs (Bruno and Tyebjee 1983, Fenn et al. 1995). One consequence of lock-in is that firms backed by the same VC must compete for follow-on funding from their initial investor (Inderst et al. 2007). This would suggest that companies may find it easier to obtain follow-on funding when peers in their portfolio suffer a negative shock.

On the other hand, Kaplan and Schoar (2005) show that flows to venture firms are sensitive to performance, which suggests at least one mechanism through which locked-in portfolio companies may be hurt when peers in their portfolio suffer a negative shock. Fund-raising 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.

This paper also relates to a strand of the banking literature that studies whether bank liquidity shocks affect bank loan supply. Shocks from various sources, including exposure to poorly performing sectors, have been shown to lead banks to decrease lending activity.[1] Less clear, however, is the extent to which these fluctuations in loan supply are smoothed by clients of affected banks. Recent evidence from matched intermediary–client data has suggested that borrowers are unable to smooth bank shocks completely, at least in emerging markets (Khwaja and Mian 2008, Schnabl 2012). As described above, given that venture firms are structured very differently than banks, it is possible that clients unrelated to a shock may actually benefit in this context.

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 10–12 years. By this time, funds must be liquidated and all distributions paid out. 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 to make new investments, it must raise a new fund periodically, usually every three to five years. Due to potential conflicts of interest, partnership agreements often 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).[2]

[1] See, e.g., Bernanke and Blinder (1992), Kashyap et al. (1993), Peek and Rosengren (1995, 1997), Kashyap and Stein (2000), Paravisini (2008), Popov and Udell (2012), and Puri et al. (2011).

[2] 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 allowed only if at least one unaffiliated fund simultaneously invests at the same price (Lerner et al. 1994).

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. Hochberg and Westerfield (2012) 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.

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. Portfolio Spillovers

Given the structure of venture capital financing just described, it is not immediately clear that a negative shock to certain companies should affect unrelated companies held in the same portfolio. However, there are several mechanisms through which this might occur. In theory, the direction of spillovers is ambiguous.

2.2.1. Relative Attractiveness of Companies Held with Others in Depressed Sector Increases. As described above, venture funds have fairly fixed financial and human capital resources and are somewhat self-contained. If the resources available to the companies in a venture portfolio do remain relatively fixed after some experience a negative shock, the shock may make it easier for unrelated companies to obtain resources. Intuitively, equalizing marginal products of investment within a portfolio, venture firms would tend to increase their allocation to companies unrelated to the shock.[3]

2.2.2. Venture Firms with High Exposure to the Depressed Sector Have Fewer Resources. On the other hand, there are several ways in which the resources available to the companies in a portfolio might decline after some suffer a negative shock. If this decline in resources is great enough, the shock may make it harder for unrelated companies to obtain resources.

In particular, when a venture firm makes initial investments, it leaves capital in reserve to fund follow-on rounds of companies that look promising but have not yet had a successful exit through an IPO or acquisition. Clearly, the amount of capital left in reserve will depend on the venture firm's assessment of the probability that its portfolio companies will have early exits. Thus, if a venture firm has high exposure to a sector in which exit becomes more difficult, the firm will find itself with more portfolio companies to support than expected and fewer reserves available per company.

There also may be fewer resources available in total, because a venture firm with fewer early exits would have less capital to recycle and also may have greater difficulty attracting syndication partners.[4] Further, it is possible that even if total resources or resources per company remain unchanged, the resources available to companies unrelated to the shock decrease, as those affected by the shock require more funding and operational support as a result.

Perhaps most importantly, when a venture firm has poor performance, this makes it more difficult for the firm to raise a new fund (Kaplan and Schoar 2005). The cross fund investing restrictions mentioned earlier often prevent such fund-raising activity from directly affecting existing portfolio companies. However, even with these restrictions, there remains an indirect channel through which existing portfolio companies can be affected by the fund-raising activity of their investors. Specifically, venture firms try to avoid having fully invested their previous fund without yet having raised their next fund. This is because, without uninvested capital available, a venture firm cannot take advantage of good investment opportunities it may come across. In addition, a firm may sustain serious damage to its reputation as a result of having missed out on the latest round of innovations. Therefore, a venture firm that is having difficulty raising a new fund has an incentive to keep its powder dry for new investments that otherwise would have been financed out of a new fund.

Thus, in theory, the effect of being held in the same portfolio as companies that experience a negative shock is ambiguous. It depends on whether the decrease in investor resources outweighs the increase

[3] The idea that, holding resources fixed, a venture firm might shift its capital allocation away from companies in a depressed sector and toward unrelated companies very much relates to the "bright side" view of internal capital markets (Stein 1997). In that sense, this paper also relates to prior work investigating how shocks to one of a diversified firm's divisions affect unrelated divisions (Lamont 1997, Houston et al. 1997, Shin and Stulz 1998). However, there are limits to this analogy. Divisions of diversified firms are locked-in contractually and are not due to informational frictions. Also, diversified firms can use cash flows from one division to invest in another, whereas venture firms cannot.

[4] Venture firms are typically allowed to recycle capital from early exits in an amount at least equal to management fees (Rossa and Tracy 2007).

in relative attractiveness for such companies. Section A of the online appendix, which is available at http://dx.doi.org./10.1287/mnsc.2014.2110, formalizes this intuition in a simple model.

2.2.3. Behavioral Mechanisms. Finally, there may also be behavioral mechanisms through which spillovers occur among companies in the same portfolio. For example, it may be that venture capitalists that invest heavily in a sector that experiences a downturn perceive that downturn differently than those that did not invest in the sector. In particular, such venture capitalists may be more likely to believe the downturn is widespread, affecting all sectors. As a result, they may slow their investment pace and become more selective (across all sectors) to a greater extent than other venture capitalists. Alternatively, those with high exposure to a depressed sector may simply overcompensate for risk-taking that did not pay off by becoming more conservative, beyond what could be rationalized by fund-raising or career concerns.[5]

2.3. Lock-In

Although venture firms with high exposure to a negative shock may indeed reduce the supply of capital to unrelated companies, it does not necessarily follow that those companies should be harmed. If they 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 that it may be difficult or 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, because venture investors are known to be deeply involved in the operations of their portfolio companies.[6] 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 because venture firms do not fail abruptly, as a result of the long-term nature of limited partner commitments. To the extent that a venture firm that is perceived to be in trouble continues to invest 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 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. Although 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, whereas others make both IT and non-IT investments. 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. Thus, the greater its investors' Internet exposure at the peak of the bubble, the more treated a company is considered to be. The pre- and postperiods 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,

[5] The authors thank an anonymous referee for pointing out these potential behavioral mechanisms.

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

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

$$h_{ijt}(\tau) = h_0(\tau)\exp(\beta_1 Post_t + \beta_2 InternetVC_{ij} + \beta_3 Post_t \times InternetExposure_{ij} + \mathbf{x}_{ijt}\boldsymbol{\beta}), \qquad (1)$$

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 $InternetExposure_{ij}$ and $Post_t$ are the treatment intensity and post indicators, respectively, and $\mathbf{x}_{\mathbf{ijt}}$ 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.[7]

It can be shown that the Cox model is equivalent to estimating a separate logit regression of the event of interest on covariates for each "failure time" in the data (limiting the sample to units still "at risk") and combining the coefficients (Kalbfleisch and Prentice 2002). 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 semiparametric.

Again, an event in this case is defined as the occurrence of a follow-on round. However, there are also competing events in this context that alter the probability of the event of interest (Gooley et al. 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.[8]

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 high Internet exposure 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 postbubble period due to other omitted or 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

[7] 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:

$$h(\tau) = \lim_{\Delta\tau \to 0} \frac{\Pr(\tau + \Delta\tau > T > \tau \mid T > \tau)}{\Delta\tau},$$

where T represents the time to the event.

[8] 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 explained 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 how a variable affects cumulative incidence. To see the 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, one could then estimate a negative coefficient on smoking in a competing risks model, because it reduces the cumulative incidence of cancer. This would not correctly reflect the positive causal relationship.

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 fund-raising (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 Reuters 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 excluded.

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 fewer than 30 days and no more than six years apart. Again, the results change little if these companies are included.

4.1. Key Measures

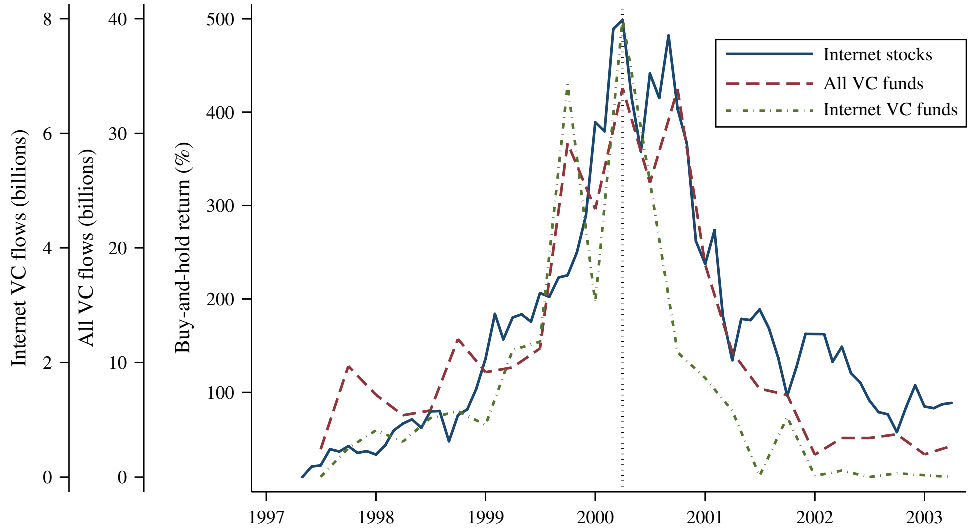
4.1.1. Dating the Peak. The postbubble period, in which the $Post_t$ indicator variable is set equal to one, is defined as all dates following March 31, 2000. This is motivated by Figure 1, which shows the buy-and-hold return on publicly traded Internet stocks. Internet stock returns are calculated as 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.[9] Quarterly flows to newly raised venture funds are also shown, both for all funds and Internet-specific funds, as categorized by Thomson Reuters.[10] Commitments are converted to real 2,000 dollars using the GDP deflator. The dotted vertical line in Figure 1 corresponds to March 31, 2000, which is the peak of all three series. Thus, not only did Internet stocks peak at this date, so did venture capital fund-raising. The estimation window is chosen accordingly to run from three years before the peak (the preperiod) to three years after the peak (the postperiod).

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 was chosen because this is the life of a typical venture fund, although results are similar if a shorter window is used (see Table C.1 in the online appendix). To limit the effect of outliers that may occur because of firms with few investments in the data, firms with fewer than five observed investments during this period are considered to have unknown

[9] 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.

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

Figure 1 **(Color online) The Technology Bubble and Venture Capital**



Notes. 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 and flows to Internet-specific funds (as categorized by Thomson Reuters) are shown. Flows are converted to real 2,000 dollars using the GDP deflator. The vertical line corresponds to the peak of all three series and is located at March 31, 2000.

Internet exposure and thus are not included in the analysis.

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 up until the current round, as in Gompers (1996). Ties are broken by the total amount invested in the company, inclusive of the current round.

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 Reuters does not make the IT/non-IT distinction based on subsector; rather, this depends on a company's use of technology. Thus, not all health-related companies are considered non-IT. In particular, Thomson Reuters 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 subsector variables, gives some comfort that the non-IT classifications are at least largely correct. In addition, Thomson Reuters provides detailed business descriptions, product keywords, 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

Table 1 Sample Composition

	All				Low exposure		High exposure	
	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
North California	485	15.02	1,012	16.67	145	9.34	320	21.74
New York Tri-State	395	12.23	694	11.44	226	14.56	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
South 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./forestry/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 services	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
Manufacturing	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
Start-up/seed	—	—	730	11.96	203	13.02	184	12.46
Total	—	—	6,104	100.00	1,559	100.00	1,477	100.00

Notes. 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 backed by syndicates in the bottom and top quartile of Internet exposure are broken down separately.

terms of companies and rounds.[11] Rounds are the relevant unit of observation in most of the analysis to follow in the next section. Panel A of Table 1 breaks down the sample by region. As speculated earlier, rounds backed by venture firms in the top quartile of Internet exposure are much more likely to be associated with portfolio companies located in Northern California than rounds in the bottom quartile. The differences in the regional distributions are confirmed by a χ^2 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, because companies change stages from round to round. The order of the stages from least developed to most is start-up/seed, early, expansion, and later. By far, the most 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

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

Table 2 Summary Statistics

	p25	p50	p75	Mean	SD	*N*
Round level						
InternetExposure (whole syndicate)	0.0735	0.173	0.270	0.192	0.154	5,908
InternetExposure (lead VC)	0.0512	0.163	0.275	0.187	0.164	5,330
Number of investors	1	2	4	2.935	2.461	6,104
VC level						
InternetExposure	0.0330	0.193	0.383	0.244	0.235	782
Number of investments	11	25.50	62	59.42	100.0	782
FirmAge	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	0.208	0.406	6,508
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	1,683

Notes. 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 United States. 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 1. 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; 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 because 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.

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.[12] 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 companies with lower Internetexposure must have funded more rounds in the data. Although not shown in Table 2, 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 Are Affected, and Non-IT Companies Are Unaffected

I begin by verifying that IT companies, particularly Internet companies, had greater difficulty raising continuation financing in the postbubble period. Were this not the case, it 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

$$h_{ijt}(\tau) = h_0(\tau)\exp(\beta_1 Post_t) \qquad (2)$$

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

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

Table 3 Single Difference

	Communications	Hardware	Software	Internet	Semiconductors
			Panel A: IT sectors		
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
	Biotech	**Consumer**	**Energy**	**Medical**	**Other non-IT**
			Panel B: Non-IT sectors		
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

Notes. This table shows the results of estimating univariate Cox proportional hazards 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 that $Post_t$ 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% levels, respectively.

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 postbubble 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 a conventional level of significance, biotech, consumer, energy, medical, and other non-IT companies all had a statistically insignificant change in hazard in the postbubble 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. Although interesting to note, this is not necessary for my identification strategy to be valid, because 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 postperiod.

5.2. Non-IT Companies Backed by VCs with High Internet Exposure Were Affected

Next, I limit the sample to non-IT companies and estimate Cox models of the form

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

separately for rounds backed by lead VCs in the top quartile and bottom quartile of Internet exposure. Figure 2 shows the estimates of α_t, which represent a full set of year fixed effects.[13] Before the peak of the bubble, continuation hazard for the companies backed by VCs with high and low Internet exposure followed roughly parallel trends. However, after 2000, the two groups diverged considerably. Note that the fact that the two groups followed parallel trends before 2000 suggests that spillovers to non-IT companies did not occur on the upside as the bubble inflated, but only on the downside as it deflated.[14]

To examine this pattern more carefully, I estimate the difference-in-differences specification of Equation (1). Table 4 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 et al. 2011). Beginning with column (1), the estimate of β_3 is negative and statistically significant. To interpret the magnitudes of

[13] To make the graph symmetric, in this case, I extend the start of the estimation window back one year (to March 31, 1996), so that a 1997 year fixed effect can be estimated with 1996 as the omitted year.

[14] This is also consistent with Table C.3 in the online appendix, which shows that, during the preperiod, non-IT portfolio companies did not become more likely to receive follow-on rounds as quarterly flows to Internet funds increased, even if their venture firm was heavily invested in the Internet sector. In contrast, during the postperiod, as Internet flows decreased, portfolio companies did become less likely to receive follow-on rounds, particularly if their venture firm was heavily invested in the Internet sector.

Table 4 Baseline Difference-in-Differences

	Whole syndicate			Lead VC		
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.0721	0.0579	0.104	0.111*	0.0803	0.190
	[0.0600]	[0.0624]	[0.117]	[0.0615]	[0.0631]	[0.134]
InternetExposure	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 × *InternetExposure*	−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

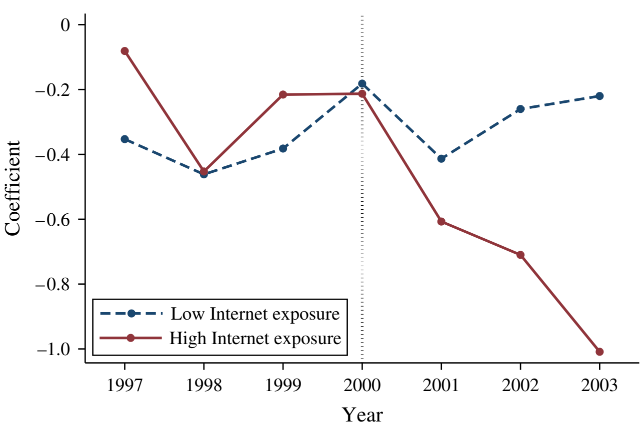
Notes. This table shows the results of estimating Cox proportional hazards models. Analysis time, τ, is defined as the time since company i raised its jth round of financing, and the event of interest is the raising of a $(j+1)th$ round. The variable $Post_t$ is an indicator equaling one if the date, t, is after the peak of the technology bubble (March 31, 2000) and zero otherwise. Note that $Post_t$ 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. The sample is restricted to financing rounds of venture-backed non-IT portfolio companies based in the United States. 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 et al. (2011).

* and ** denote statistical significance at the 10% and 5% levels, respectively.

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%. Thus, the economic magnitude of the estimated effect is quite substantial.

In column (2) of Table 4, 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, because 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-exposed syndicate. After these controls were added, 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-exposed 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)–(6), I estimate the same specifications as in the first three columns but define the variable $InternetExposure_{ij}$ based on the Internet exposure of only the lead venture firm in the round. This gives rise to similar results.

Figure 2 (Color online) Parallel Trends



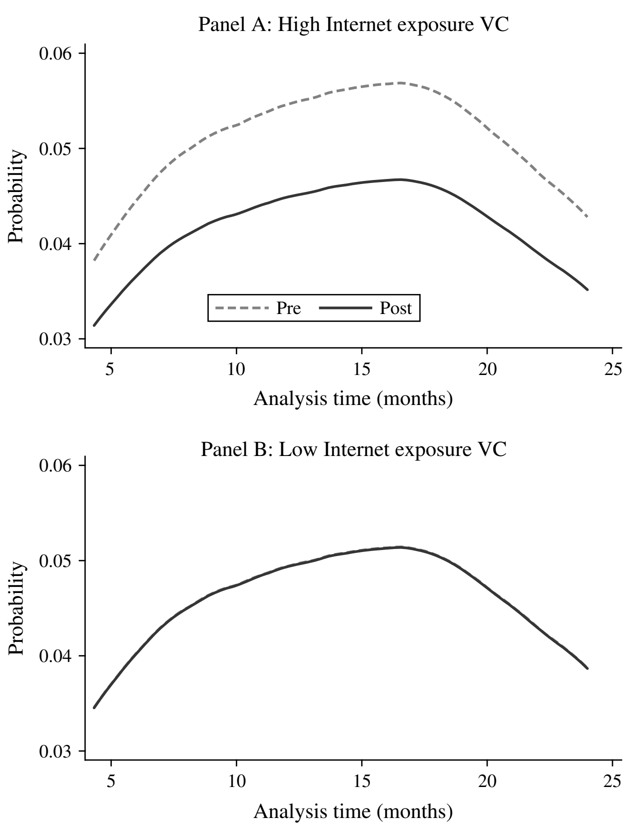
Notes. This figure depicts the result of estimating Cox models of the form

$$h_{ijt}(\tau) = h_0(\tau)\exp(\alpha_t)$$

separately for rounds backed by VCs in the top quartile and bottom quartile of Internet exposure, where α_t represents year fixed effects. The estimated coefficients are shown. To make the graph symmetric around 2000, the estimation window starts on March 31, 1996, so that a 1997 year fixed effect can be estimated (with 1996 as the omitted year).

As previously mentioned, 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 recovered. 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 4. It appears that the baseline hazard function conforms to an inverted-U shape. This makes sense because, immediately after 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, because the fact that the company has not received another round begins to indicate that it will never receive one. The proportional shifts in the baseline hazard simply reflect the estimated coefficients just discussed. The figure shows graphically that non-IT companies backed by syndicates with *InternetExposure* at the 75th percentile experienced a decrease in continuation hazard in the postbubble period (panel A), whereas those backed by syndicates with *InternetExposure* at the 25th percentile experienced a statistically insignificant change (panel B). The difference in these differences is essentially the estimated treatment effect.

Figure 3 **Smoothed Hazard Function**



Notes. This figure depicts the results from column (1) of Table 4 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. Panel A shows the shift in the hazard function associated with the end of the bubble for a company backed by a VC syndicate with Internet exposure at the 75th percentile (27% Internet exposure). Panel B shows the shift in the hazard function associated with the end of the bubble for a company backed by a VC syndicate with Internet exposure at the 25th percentile (7.35% Internet exposure). A smoothed estimate of the baseline hazard function is recovered (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.

5.2.1. Robustness. One concern at this point is that some of the companies classified by Thomson Reuters 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 portfolio companies backed by venture firms with Internet investments tended to be miscategorized 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 subsamples that are less likely to include IT-related companies. Table C.2 in the online appendix replicates column (6) of Table 4 excluding (1) all non-IT companies classified by Thomson Reuters as "Consumer Related"; (2) all non-IT companies producing "Other Products"; (3) 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; and (4) all companies that are categorized as IT by Dow Jones' VentureSource database.[15] In all cases, the results remain similar.

5.2.2. Other Outcomes. The primary outcome examined in this paper is the (instantaneous) probability of raising a new round of VC funding. However, one may also be interested in whether spillovers across portfolio companies manifest themselves in terms of other outcomes, such as the probability of company failure or success. Going too long without a follow-on round of financing typically leads venture-backed companies to go defunct. Thus, in terms of real effects, the estimates presented thus far do likely imply that non-IT companies backed by VCs

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

Table 5 Other Outcomes

	Failure			Success		
	(1)	(2)	(3)	(4)	(5)	(6)
Post	−0.163	−0.0184	0.111	−0.298**	−0.280**	−0.194
	[0.103]	[0.105]	[0.256]	[0.130]	[0.129]	[0.298]
InternetExposure	−0.248	−0.184	−0.162	−0.000247	0.0835	0.0615
	[0.315]	[0.318]	[0.323]	[0.386]	[0.387]	[0.387]
Post × *InternetExposure*	1.314**	0.978**	0.968**	0.148	0.0356	0.241
	[0.391]	[0.394]	[0.408]	[0.536]	[0.531]	[0.546]
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	2,758	2,726	2,726	2,758	2,726	2,726

Notes. This table replicates columns (4)–(6) of Table 4 now defining the event of interest as failure/success and defining spells at the company level rather than the round level. A company is considered to have failed if its status is described as bankrupt or defunct. It is also considered to have failed if its status is described as active, but it has not raised a new round of financing for six years or more. A company is considered to have succeeded if its status is described as public, merged, or acquired. When a company has an unknown failure date, it is assumed to have failed two years after the final financing round. Spells are censored at competing risk dates. That is, when failure is the event of interest, spells are censored at the date of success. When success is the event of interest, spells are censored at the date of failure. The sample is restricted to financing rounds of venture-backed non-IT portfolio companies based in the United States. 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 lead venture firm.

**Denotes statistical significance at the 5% level.

with high Internet exposure had a significantly larger increase in their failure rate than others.

It is also possible to examine company failure more directly by again estimating the difference-in-differences specification of Equation (1), now defining the event of interest as failure and defining spells at the company level rather than the round level. However, one issue is that the date at which a company fails is often unknown. Indeed, this is one of the reasons that I focus primarily on the probability of a new financing round, because these always occur at known dates. When a company that ultimately failed has an unknown failure date, I simply assume that it failed two years after the final financing round. Although there is clearly measurement error involved in this procedure, there is no reason to expect that it should bias the estimates upward. As before, I censor spells at competing risk dates—in this case, where a company went public or was acquired.

Results are shown in columns (1)–(3) of Table 5. The coefficient on the interaction term is estimated to be positive and statistically significant, indicating that non-IT companies backed by lead VCs with high Internet exposure indeed had a larger increase in their probability of failure than others when the bubble burst. This is consistent with the idea that the inability to raise further financing led to company failure. I also repeat the same exercise in columns (4)–(6) of Table 5 but with company success (i.e., IPO or acquisition) as the event of interest. Here, the interaction term is statistically insignificant across all specifications, indicating that non-IT companies backed by VCs with high Internet exposure did not experience a differential change in their probability of success. Thus, although companies backed by VCs with high Internet exposure became more likely to fail, conditional on not failing, they were no more or less likely at any point in time to have an IPO or acquisition.[16]

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

It still remains possible that non-IT companies backed by more Internet-exposed venture firms differed from others along some unobservable dimension that made them worse investments in the postbubble 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

[16] Given that failure precludes success in this context, one may be tempted to think that any variable associated with an increase in failure should also be associated with a decrease in success. However, that is not the case, given again that I am estimating the effect of covariates on cause-specific hazard by censoring at competing risk dates (Pintilie 2007).

Table 6 Effect of Internet Exposure on VC Dropout

	OLS		Company FE	
	(1)	(2)	(3)	(4)
InternetExposure	−0.00316	−0.0321	−0.00743	−0.0182
	[0.0628]	[0.0599]	[0.0622]	[0.0623]
Post	−0.0169	−0.0994**	0.139**	0.113**
	[0.0203]	[0.0334]	[0.0218]	[0.0265]
Post × *InternetExposure*	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

Notes. This table shows the results of estimating models of the form

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

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, because 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 United States. 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 et al. (2011).

**Denotes statistical significance at the 5% level.

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.[17]

[17] 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, and its omission is taken to be a data error.

I then estimate linear probability models of the form

$$VCDropout_{ijkt} = \alpha_i + \beta_1 Post_t + \beta_2 InternetExposure_k + \beta_3 Post_t \times InternetExposure_k, \qquad (3)$$

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 6 reports the results. Because $InternetExposure_k$ varies only at the venture firm level, standard errors are clustered accordingly by venture firm as well as portfolio company. In the first two columns, Equation (3) 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 an increase of one standard deviation 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 that a firm dropped out in the preperiod was only 10.8%, these magnitudes are again economically meaningful, because they represent a percentage increase of 38.5. This provides perhaps the clearest evidence that venture firms with high Internet exposure ceased to support companies that they would have liked to continue to support.[18] Although these results do imply that some companies were able to overcome lack of participation from previous investors, 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.

Finally, although this test provides fairly convincing evidence against many alternative stories, it should be noted that it does have certain limitations. In particular, even for the same company, it is possible that Internet-exposed investors viewed the company as more Internet-related than others. For example, one could imagine that an Internet-exposed venture capitalist might invest in a distribution company because it believes that the company can grow due to e-commerce. At the same time, a non-Internet-exposed venture capitalist may invest in the company because it believes it can grow as a result of increasing demand from China. Following the crash, the Internet-exposed venture capitalists might drop out, whereas the non-Internet-exposed venture capitalist might remain as an investor. However, in this case it would not be because of spillovers from other portfolio companies.[19]

5.4. Internet VCs Had Increased Fund-Raising Difficulty After the Collapse

Next, I explore the mechanism underlying these results. As discussed earlier, one important mechanism through which contagion might occur is the transmission of fund-raising 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 hazard models at the 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. Results are shown in Table 7. In column (1), I repeat the basic specification of Table 4. In column (2), I limit the sample to the extreme quartiles of the distribution of VC Internet exposure. In this case, the variable $InternetVC_k$ is an indicator variable equal to one if the venture firm is in the top quartile. In column (3), I replace the $Post_t$ indicator with the log of $InternetFlows_t$, the quarterly flows to Internet-specific venture funds shown in Figure 1.

Table 7 The Effect of Internet Exposure on VC Fund-Raising

	(1)	(2)	(3)
Post	−0.182*	0.0445	
	[0.0960]	[0.143]	
InternetExposure	0.534**		0.0182
	[0.205]		[0.221]
Post × *InternetExposure*	−0.875**		
	[0.259]		
InternetVC		0.438**	
		[0.184]	
Post × *InternetVC*		−0.645**	
		[0.188]	
log(*InternetFlows*)			0.200**
			[0.0692]
log(*InternetFlows*) × *InternetExposure*			0.321**
			[0.102]
Spells	1,428	716	1,428

Notes. This table estimates the hazard of a venture firm raising a follow-on fund from limited partners. Analysis time, τ, is defined as the time since venture firm k raised its last fund. Column (1) repeats the basic specification of Table 4. Column (2) limits the sample to the extreme quartiles of the distribution of VC Internet exposure. In this case the variable $InternetVC_k$ is an indicator variable equal to one if the venture firm is in the top quartile. Column (3) replaces the $Post_t$ indicator with the log of $InternetFlows_t$, the quarterly flows to Internet-specific venture funds shown in Figure 1. 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 et al. (2011).

* and ** denote statistical significance at the 10% and 5% levels, respectively.

The same general pattern emerges as did at the portfolio company level. The coefficients on the interaction terms $Post_t \times InternetExposure_k$ and $Post_t \times InternetVC_k$ are both estimated to be negative, whereas 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 fund-raising 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 (2) imply that venture firms in the top quartile of Internet exposure had a 47.5% larger decrease in fund-raising hazard than those in the bottom quartile.

[18] 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 a result of selection, because companies that received follow-on rounds in the post-bubble period may have been of higher quality and thus experienced fewer investor dropouts.

[19] The authors thank an anonymous referee for pointing out this alternative story.

Table 8 **Heterogeneity in the Effect of VC Internet Exposure**

	Lead VC any age	Lead VC age < 6 years	Lead VC age ≥ 6 years
	(1)	(2)	(3)
Post	0.0560	−0.245	0.124
	[0.155]	[0.250]	[0.171]
InternetExposure	0.0282	−0.491	−0.0865
	[0.439]	[0.722]	[0.518]
YearsSinceRaised	−0.0153	−0.0807	−0.0126
	[0.0231]	[0.131]	[0.0242]
Post × *InternetExposure*	0.0670	1.355*	−0.480
	[0.508]	[0.801]	[0.627]
Post × *YearsSinceRaised*	0.0419	0.150	0.0104
	[0.0348]	[0.134]	[0.0422]
InternetExposure × *YearsSinceRaised*	0.0278	0.532	−0.00496
	[0.114]	[0.442]	[0.127]
Post × *InternetExposure* × *YearsSinceRaised*	−0.514**	−1.402**	−0.228
	[0.200]	[0.503]	[0.234]
Region FE	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
Post × *Region FE*	Yes	Yes	Yes
Post × *Sector FE*	Yes	Yes	Yes
Post × *Stage FE*	Yes	Yes	Yes
InternetExposure × *Stage FE*	Yes	Yes	Yes
Post × *InternetExposure* × *Stage FE*	Yes	Yes	Yes
Spells	4,372	1,030	3,320

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

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

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. Column (3) shows results for rounds backed by lead venture firms less than six years old at the peak. Column (3) shows results for rounds backed by lead venture firms at least 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 et al. (2011).

* and ** denote statistical significance at the 10% and 5% levels, respectively.

5.5. Companies Backed by Young VCs Late in the Fund-Raising Cycle Were Most Affected

Thus, Internet-exposed 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 postbubble period. Although these two facts would appear to be 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 as a result of the diminished fund-raising 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 fund-raising capacity.

To test this, I reestimate the specifications of Table 4, 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.[20]

Results are reported in column (1) of Table 8. The primary coefficient of interest is that on the triple interaction term $Post_t \times InternetExposure_{ij} \times$

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

$YearsSinceRaised_{ijt}$, which is estimated to be negative and statistically significant. This suggests that the negative effect of the bubble's collapse on portfolio companies backed by firms with high Internet exposure 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 hypothesis 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 fund-raising 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. 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 fund-raising difficulties were indeed driving the baseline results. Indeed, the model presented in Section A of the online appendix predicts that contagion should occur only if fund-raising is sufficiently sensitive to performance, which would more likely be true for young venture firms.

I therefore reestimate column (1), 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.[21] Results are presented in columns (2) and (3). The primary coefficient of interest is again that on the triple interaction term $Post_t \times InternetExposure_{ij} \times YearsSinceRaised_{ijt}$. In column (2), this coefficient is estimated to be negative and statistically significant for the $YoungVC_{ij} = 1$ subgroup. In column (3), 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. Therefore, to summarize, the non-IT 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 fund-raising mechanism's playing an important role. However, it is certainly possible that the other potential mechanisms discussed in §2.2 were also at play simultaneously. Unfortunately, these alternative mechanisms are more difficult to examine empirically due to data limitations.

5.6. Companies Backed by Internet VCs Were No Less Productive Before the 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 that 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 net present value (NPV).[22] 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, because 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 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 et al. 2001). These data are then matched with VentureXpert on company name,

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

[22] This again parallels the internal capital market literature. Although 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 et al. (2000), Whited (2001), and Chevalier (2004).

Table 9 VC Internet Exposure and Patent Productivity

	Whole syndicate		Lead VC	
	(1) Total patents	(2) Relative citations	(3) Total patents	(4) Relative citations
InternetExposure	1.890 [2.215]	2.497 [3.664]	0.458 [2.541]	0.973 [3.360]
Region FE	Yes	No	Yes	No
Sector FE	Yes	No	Yes	No
Observations	443	1,574	419	1,456

Notes. This table shows the results of estimating equations of the form

$$\lambda_i = \exp(\beta_0 + \beta_1 \mathit{InternetExposure}_i + \mathbf{x}_{ijt}\boldsymbol{\beta}),$$

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 because 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, because 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 et al. (2011). The variable γ_i represents the mean number of citations received (in the first three years) for all patents with the same U.S. Patent and Trademark Office 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 $\mathit{InternetExposure}_i$ 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 et al. (2011).

using the name standardization and matching procedures developed by the NBER Patent Data Project.[23] Matches are confirmed manually. I then limit the sample to companies that raised their first round of financing in the three years before 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. As in Lerner et al. (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

$$\lambda_i = \exp(\beta_0 + \beta_1 \mathit{InternetExposure}_i + \mathbf{x}_{ijt}\boldsymbol{\beta}), \tag{4}$$

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.[24]

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

[24] 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. 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 et al. (2011).

Results are reported in Table 9 with coefficients reported in terms of mean marginal effects to ease interpretation. Across all specifications, the coefficient on $\mathit{InternetExposure}_i$ is estimated to be positive but statistically insignificant. Thus, I fail to reject the null hypothesis that the number or quality of patents a company issued before the collapse of the bubble and the Internet exposure of its investors were unrelated. If anything, the point estimates suggest that firms with high Internet exposure invested in more innovative non-IT companies.

6. Conclusion

This paper attempts to shed light on whether companies in a venture portfolio become artificially linked as a result of sharing a common investor. 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 to participate in follow-on rounds. Exploring the mechanism underlying these results, I find that Internet-exposed venture firms suffered a larger decline in their fund-raising 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-exposed venture firms were of lower quality.

These findings have important implications for both entrepreneurs and venture capitalists. For entrepreneurs, they suggest that not only is it important to consider an investor's ability to add value through operational support and governance, it is also important to consider the investor's other portfolio companies and how they may impact follow-on financing. This increases the need for reverse due diligence. For venture capitalists, the findings suggest that each investment comes with a potential externality in the sense that negative shocks to certain portfolio companies may cause subsequent underinvestment in others. This makes the venture capitalist's portfolio problem more complicated.

Overall, this paper highlights the finding that, in order to understand venture investment, it is crucial to take into account the fact that venture firms invest in portfolios of multiple companies. Shocks to portfolios' peers can significantly affect the continuation financing decisions that ultimately determine whether a company survives.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mnsc.2014.2110.

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References

Admati AR, Pfleiderer P (1994) Robust financial contracting and the role of venture capitalists. *J. Finance* 49(2):371–402.

Baker M, Gompers PA (2003) The determinants of board structure at the initial public offering. *J. Law Econom.* 46(2):569–598.

Bernanke BS, Blinder AS (1992) The federal funds rate and the channels of monetary transmission. *Amer. Econom. Rev.* 82(4):901–921.

Brunnermeier MK, Nagel S (2004) Hedge funds and the technology bubble. *J. Finance* 59(5):2013–2040.

Bruno AV, Tyebjee TT (1983) The One That Got Away: A Study of Ventures Rejected by Venture Capitalists. Hornaday JA, Timmons JA, Vesper KH, eds. *Proc. 1983 Conf. Entrepreneurship Babson College* (Center for Entrepreneurial Studies, Babson College, Wellesley, MA), 289–306.

Cameron AC, Trivedi PK (1998) *Regression Analysis of Count Data* (Cambridge University Press, Cambridge, UK).

Cameron AC, Gelbach JB, Miller DL (2011) Robust inference with multiway clustering. *J. Bus. Econom. Statist.* 29(2):238–249.

Chevalier J (2004) What do we know about cross-subsidization? Evidence from merging firms. *B.E. J. Econom. Anal. Policy* 4(1), http://dx.doi.org/10.2202/1538-0637.1218.

Fenn GW, Liang N, Prowse S (1995) The economics of the private equity market. Staff Studies Series 168, Board of Governors of the Federal Reserve System, Washington, DC.

Fine JP, Gray RJ (1999) A proportional hazards model for the subdistribution of a competing risk. *J. Amer. Statist. Assoc.* 94(446):496–509.

Gompers PA (1995) Optimal investment, monitoring, and the staging of venture capital. *J. Finance* 50(5):1461–1489.

Gompers PA (1996) Grandstanding in the venture capital industry. *J. Financial Econom.* 42(1):133–156.

Gompers PA, Lerner J (2000) Money chasing deals? The impact of fund inflows on private equity valuation. *J. Financial Econom.* 55(2):281–325.

Gompers P, Kovner A, Lerner J (2009) Specialization and success: Evidence from venture capital. *J. Econom. Management Strategy* 18(3):817–844.

Gooley TA, Leisenring W, Crowley J, Storer BE (1999) Estimation of failure probabilities in the presence of competing risks: New representations of old estimators. *Statist. Medicine* 18(6):695–706.

Greenwood R, Nagel S (2009) Inexperienced investors and bubbles. *J. Financial Econom.* 93(2):239–258.

Hall B, Jaffe A, Trajtenberg M (2001) The NBER patent citations data file: Lessons, insights and methodological tools. NBER Working paper 8498, National Bureau of Economic Research, Cambridge, MA.

Hellmann T, Puri M (2000) The interaction between product market and financing strategy: The role of venture capital. *Rev. Financial Stud.* 13(4):959–984.

Hellmann T, Puri M (2002) Venture capital and the professionalization of start-up firms: Empirical evidence. *J. Finance* 57(1):169–197.

Hochberg YV, Westerfield MM (2012) The size and specialization of direct investment portfolios. Working paper, Rice University, Houston, TX.

Houston J, James C, Marcus D (1997) Capital market frictions and the role of internal capital markets in banking. *J. Financial Econom.* 46(2):135–164.

Hsu DH (2004) What do entrepreneurs pay for venture capital affiliation? *J. Finance* 59(4):1805–1844.

Inderst R, Mueller HM, Münnich F (2007) Financing a portfolio of projects. *Rev. Financial Stud.* 20(4):1289–1325.

Jensen MC (1986) Agency costs of free cash flow, corporate finance, and takeovers. *Amer. Econom. Rev.* 76(2):323–329.

Kalbfleisch JD, Prentice RL (2002) *The Statistical Analysis of Failure Time Data* 2nd ed. (Wiley-Interscience, Hoboken, NJ).

Kaplan SN, Schoar A (2005) Private equity performance: Returns, persistence, and capital flows. *J. Finance* 60(4):1791–1823.

Kaplan SN, Strömberg P (2003) Financial contracting theory meets the real world: An empirical analysis of venture capital contracts. *Rev. Econom. Stud.* 70(2):281–315.

Kaplan SN, Strömberg P (2004) Characteristics, contracts, and actions: Evidence from venture capitalist analyses. *J. Finance* 59(5):2177–2210.

Kashyap AK, Stein JC (2000) What do a million observations on banks say about the transmission of monetary policy? *Amer. Econom. Rev.* 90(3):407–428.

Kashyap AK, Stein JC, Wilcox DW (1993) Monetary policy and credit conditions: Evidence from the composition of external finance. *Amer. Econom. Rev.* 83(1):78–98.

Khwaja AI, Mian A (2008) Tracing the impact of bank liquidity shocks: Evidence from an emerging market. *Amer. Econom. Rev.* 98(4):1413–1442.

Lamont O (1997) Cash flow and investment: Evidence from internal capital markets. *J. Finance* 52(1):83–109.

Lerner J (1995) Venture capitalists and the oversight of private firms. *J. Finance* 50(1):301–318.

Lerner J, Hardymon F, Leamon A (1994) Note on private equity partnership agreements. HBS 9-294-084, Harvard Business School, Boston, MA.

Lerner J, Sorensen M, Strömberg P (2011) Private equity and long-run investment: The case of innovation. *J. Finance* 66(2): 445–477.

Paravisini D (2008) Local bank financial constraints and firm access to external finance. *J. Finance* 63(5):2161–2193.

Peek J, Rosengren E (1995) The capital crunch: Neither a borrower nor a lender be. *J. Money Credit Banking* 27(3):625–638.

Peek J, Rosengren ES (1997) The international transmission of financial shocks: The case of Japan. *Amer. Econom. Rev.* 87(4):495–505.

Pintilie M (2007) Analysing and interpreting competing risk data. *Statist. Medicine* 26(6):1360–1367.

Popov A, Udell GF (2012) Cross-border banking and the international transmission of financial distress during the crisis of 2007–2008. *J. Internat. Econom.* 87(1):147–161.

Puri M, Rocholl J, Steffen S (2011) Global retail lending in the aftermath of the U.S. financial crisis: Distinguishing between supply and demand effects. *J. Financial Econom.* 100(3):556–578.

Rajan RG (1992) Insiders and outsiders: The choice between informed and arm's-length debt. *J. Finance* 47(4):1367–1400.

Rajan R, Servaes H, Zingales L (2000) The cost of diversity: The diversification discount and inefficient investment. *J. Finance* 55(1):35–80.

Rossa J, Tracy T (2007) *Private Equity Partnership Terms and Conditions* 5th ed. (Dow Jones, Wellesley, MA).

Scharfstein DS (1998) The dark side of internal capital markets II: Evidence from diversified conglomerates. NBER Working paper 6352, National Bureau of Economic Research, Cambridge, MA.

Schnabl P (2012) The international transmission of bank liquidity shocks: Evidence from an emerging market. *J. Finance*. 67(3):897–932.

Sharpe SA (1990) Asymmetric information, bank lending and implicit contracts: A stylized model of customer relationships. *J. Finance* 45(4):1069–1087.

Shin H-H, Stulz RM (1998) Are internal capital markets efficient? *Quart. J. Econom.* 113(2):531–552.

Stein JC (1997) Internal capital markets and the competition for corporate resources. *J. Finance* 52(1):111–133.

Whited TM (2001) Is it inefficient investment that causes the diversification discount? *J. Finance* 56(5):1667–1691.