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Propagation of Financial Shocks: The Case of Venture Capital

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Abstract

The non-transferable information that financial intermediaries accumulate about their investments can lead portfolio companies to become locked-in. As a result, companies can become vulnerable to exogenous fluctuations in the health of their intermediaries. I study these issues in the context of venture capital, where informational problems are particularly severe. Specifically, I investigate the effect of the collapse of the technology bubble on non-IT companies that were financed by venture firms with high exposure to the internet sector. Using semi-parametric survival analysis, I estimate that the end of the bubble was associated with a 26% larger decline in the hazard of raising a follow-on round for these non-IT companies in comparison to others. Moreover, when these companies did raise follow-on rounds, they were more likely to do so without the participation of their previous backers, suggesting that internet-focused venture firms indeed became more selective due to poor financial health. Exploring the underlying mechanism, I find that internet-focused venture firms suffered a larger decline in their fundraising capacity during this period, which may have been transmitted to their portfolio companies. Consistent with this, I estimate that the negative effect of a venture firm's internet exposure on its portfolio companies was strongest for young venture firms that had not raised a new fund recently. Finally, examining patent productivity before the collapse of the bubble, I find no evidence that non-IT companies backed by internet-focused venture firms were of lower quality.

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1 Introduction

Financial intermediaries channel funds from dispersed investors to entities in need of capital. The potential benefits of intermediation are well documented; however, their use also comes with potential downsides. Perhaps chief among these is the danger that intermediary capital may become impaired. When an intermediary faces distress, this can have a negative impact on previous recipients of that intermediary's capital, as financial frictions may make it difficult for clients to switch intermediaries. A client affiliated with a distressed intermediary must incur direct search costs to find a potential replacement. Potential replacements may also face a form of the winner's curse in bidding against a better-informed incumbent (Sharpe, 1990; Rajan, 1992). Finally, even if there is no winner's curse in operation, valuable non-transferable information is likely destroyed when intermediary-client relationships are severed. These frictions, which largely result from intermediary monitoring, all contribute to client lock-in.

To the extent that intermediary clients become locked-in, they may also become artificially linked with other investments held in the same intermediary portfolio, even if those investments are unrelated based on fundamentals. For example, if an intermediary invests heavily in a sector that performs poorly, it may then have to decrease the supply of capital available to its clients in unrelated sectors. In this paper, I investigate whether financial shocks propagate across sectors in this manner in the context of venture capital intermediaries.

Financial frictions engendered by intermediary monitoring are likely to be particularly strong in the venture capital setting. There is a large literature documenting the enormous amount of post-investment monitoring and advising that venture capitalists engage in relative to other intermediaries. By working so closely with the management teams of their portfolio companies, venture firms are likely to accumulate a large amount of private information about their investments. Moreover, in many cases this information is likely "soft," in the spirit of Stein (2002), meaning that it could not be credibly transmitted even if it were desirable to do so. While the intensive monitoring activity associated with venture capital makes it possible for opaque companies to access capital, it also makes these companies more vulnerable to fluctuations in their intermediaries' financial health.

Not only are financial frictions likely strong in the venture capital setting, they are also likely of great consequence. For mature companies, disruptions in intermediary relationships may be harmful but survivable. For a typical venture-backed company on the other hand, with negative earnings and few tangible assets, these disruptions are likely to lead to liquidation. Such liquidations are especially consequential given the nature of the companies financed by venture firms. Four of the twenty largest companies in the U.S. by market capitalization—Apple, Google, Microsoft, and Cisco—were backed by venture funds in their early days. In addition, over 60% of the IPOs that have occurred since 1999 have been venture-backed (Kaplan and Lerner, 2010). To the extent that venture firms provide capital to innovative companies with the potential to create large social surpluses, distortions in their decision-making could have important social implications.

Finally, in the venture capital setting, it is possible to observe each venture firm's exposure to various sectors, each portfolio company's ability to raise continuation financing, and the links between portfolio companies and venture firms. This makes it possible to investigate whether companies have increased difficulty raising follow-on rounds when their previous investors suffer due to exposure to a declining sector. Without matched data of this kind, it is challenging to determine whether clients of intermediaries that experience adverse shocks are able to smooth out these shocks by obtaining capital from alternative sources. Matched intermediary-client data have been difficult to obtain in other settings, although recent research has made progress in this direction (Khwaja and Mian, 2008; Jiménez, Ongena, Pedró, and Saurina, 2010; Schnabl, 2010).

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 particular, I exploit variation in the degree of a venture firm's exposure to the internet sector. This variation largely results from the fact that some firms specialize in non-IT investments, while others diversify across several sectors. The basic premise is that if a non-IT company's backers had high exposure to the internet sector, that company might have had greater difficulty in raising follow-on rounds after the technology bubble burst.

I use semi-parametric survival analysis to estimate the effect of various factors on the "hazard" of raising a follow-on round. The most basic specification can be thought of as analogous to a difference-in-differences estimation framework. In this case, a company is considered to be in the treatment group if its backers invested heavily in internet companies during the years leading up to the peak of the technology bubble. Similarly, a company is considered to be in the control group if its backers invested little in the internet sector during that time. I estimate that non-IT companies in the treatment group experienced a 26% larger decline in continuation hazard with the collapse of the bubble than did those in the control group. Similar results obtain if a continuous variable is used to measure the internet exposure of venture firms (rather than a treatment indicator based on this variable), as well as if aggregate quarterly flows into internet venture funds are used to measure the state of the venture-backed internet sector (rather than an after indicator based on this variable). Moreover, while continuation hazard declined for treated companies as the bubble deflated, it did not increase as the bubble inflated. Thus, it does not appear that the baseline results are driven by hazard having been "too high" for these companies during the bubble.

The primary concern with this identification strategy is that non-IT companies backed by internet-focused venture firms may have differed from others in ways that made them worse investments in the post-bubble period. While it seems unlikely that the prospects of a biotech company would directly relate to internet technologies, other stories are certainly plausible. For example, companies backed by internet-focused venture firms may have been disproportionately located in Northern California and suffered due to a decline in the local economy.

I address these endogeneity concerns in several ways. First, I include a large set of controls to account for the fact that some non-IT companies may have suffered more than others when the bubble burst, due to observable characteristics. Controlling for these factors does not substantially change the estimated effect of internet exposure. Second, I limit attention only to follow-on rounds that were successfully raised. During normal times, it is relatively uncommon for a venture firm that has already invested in a company not to participate in a follow-on round of that company. Noting this, I examine whether venture firms with greater internet exposure had a greater increase (from before to after the peak of the bubble) in their probability of dropping out of a round. I find that, for an average venture firm, a one standard deviation increase in internet exposure led to a 27.1% larger increase in the probability of dropping out. This would not be predicted if the baseline results were driven entirely by company characteristics. Indeed, the fact that internet-focused venture firms became less likely to participate, even in rounds deemed by others to have been merited, suggests that these firms became more selective as a result of poor financial health.

Next, I explore the mechanism underlying these results. One reason that poor performance in one part of a venture firm's portfolio might affect continuation financing decisions in another part is that poor performance may lead to increased difficulty in raising new funds from limited partners. I confirm that for an average venture firm, a one standard deviation increase in internet exposure was associated with an additional 12.54% decrease in fundraising hazard when the bubble burst. Such fundraising difficulties would directly affect existing portfolio companies if they otherwise would have been refinanced out of a new fund. Furthermore, even if cross-fund investing were precluded, a venture firm having trouble raising a new fund would likely still become more selective with its existing capital, in order to "keep its powder dry" for new potential investments. This would lead existing portfolio companies to be indirectly affected.

A venture firm that had not raised a new fund from limited partners recently would likely be more concerned about a decline in its fundraising capacity (due to internet exposure) than a firm that just raised a new fund. Likewise, a young firm with a short investment track record would likely be more concerned than a well-established firm. Thus, if venture firm fundraising were driving the baseline results, one would expect the negative effect of a venture firm's internet exposure on its portfolio companies would be strongest for young venture 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 the non-IT companies funded by internet-focused venture firms during the bubble tended to be of lower quality. Specifically, I test whether the patent productivity of these companies was lower, prior to the collapse of the bubble. If this were true, the decline in continuation hazard suffered by these companies might not have been entirely inefficient. I find no evidence, however, that companies backed by venture firms with high internet exposure were less productive in terms of the number of patents they produced or the number of citations those patents received.

This paper relates perhaps most directly to a strand of the banking literature that studies the effect of a bank's health on the value of its borrowers. Several papers make use of the event study methodology to estimate abnormal returns for clients of distressed banks following announcements of distress (Slovin, Sushka, and Polonchek, 1993; Yamori and Murakami, 1999; Bae, Kang, and Lim, 2002; Ongena, Smith, and Michalsen, 2003; Djankov, Jindra, and Klapper, 2005). Others examine client returns during periods of more general bank distress, exploiting cross-sectional variation in companies' bank dependency (Kang and Stulz, 2000; Chava and Purnanandam, 2009) or banks' exposure to depressed assets (Gan, 2007). With the exception of Bae, Kang, and Lim (2002), these studies find that bank distress leads to a significant decline in client value. Some of these papers also find that bank capital shocks have real consequences for clients in the form of decreased investment (Gibson, 1995; Kang and Stulz, 2000; Gan, 2007; Chava and Purnanandam, 2009).

A distinct but closely related strand of literature studies whether bank liquidity shocks affect bank loan supply. Shocks from changes in monetary policy (Bernanke and Blinder, 1992; Kashyap, Stein, and Wilcox, 1993; Kashyap and Stein, 2000; Kishan and Opiela, 2000) as well as other sources (Peek and Rosengren, 1995, 1997; Paravisini, 2008; Popov and Udell, 2010; Puri, Rocholl, and Steffen, 2010) have been shown to lead banks to decrease their lending activity. Less clear, however, is the extent to which these fluctuations in loan supply are smoothed out by clients of affected banks. Indirect evidence on this issue has led to mixed results (Bernanke, 1983; Gertler and Gilchrist, 1994; Kashyap, Lamont, and Stein, 1994; Peek and Rosengren, 2000; Ashcraft, 2006), while more direct evidence from matched data has recently suggested that borrowers are unable to smooth bank shocks completely (Khwaja and Mian, 2008; Jiménez, Ongena, Pedró, and Saurina, 2010; Schnabl, 2010).

Finally, this paper also relates to the extensive literature on venture capital. Many researchers 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 lock-in. Kaplan and Schoar (2005) show that flows to venture firms are sensitive to past performance, which suggests at least one mechanism through which locked-in portfolio companies may be hurt when their backers have high exposure to a sector that experiences a downturn. 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.

The rest of this paper proceeds as follows. Section 2 provides background on the basic features of the venture capital industry, which motivate the subsequent analysis. Section 3 discusses the empirical strategy used. Section 4 discusses the data and construction of key variables. Section 5 presents the results. Section 6 concludes.

2 Background

Before turning to the empirical strategy used in this paper, I first briefly discuss the basic features of the venture capital industry and the potential mechanisms by which shocks to one sector might propagate to another, given these features.

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 ten to twelve years. After this time, funds must be liquidated and final profits must be distributed.

Venture funds are typically close-ended in the sense that once a fund is launched it will not raise further commitments from investors. Therefore, in order for a venture firm to survive and continue making new investments it must raise a new fund periodically, usually every three to five years. Due to potential conflicts of interest, partnership agreements often limit the extent to which a venture firm can use a new fund to finance a portfolio company from a previous fund.

There is considerable heterogeneity in the investment strategies of venture capital firms. Some firms specialize in making investments within a particular sector, while others diversify across several sectors (Gompers, Kovner, and Lerner, 2009). Domain Associates, for example, is a specialist firm that focuses on life sciences. Alta Partners, on the other hand, is a generalist firm with investments in both life sciences and information technology. Generalist firms are often composed of specialist partners (Gompers, Kovner, and Lerner, 2009). During the technology bubble, it was very tempting for generalist firms to invest heavily in internet companies, as these companies were easy to take public.

The structure of financing for venture-backed portfolio companies parallels that of their financiers. Just as venture capital firms must periodically raise new funds from limited partners, venture-backed portfolio companies must periodically raise new rounds of financing from their venture capitalists. Venture firms intentionally give their portfolio companies insufficient funding, so that these companies will have to return for follow-on rounds. Failure to raise a follow-on round generally leads to liquidation; therefore, many have interpreted staged financing as a way of mitigating agency problems by implicitly giving venture capitalists the ability to liquidate in bad states of the world (Gompers, 1995; Kaplan and Strömberg, 2003).

One final aspect of venture capital financing that is relevant in the context of this paper is that investments are often syndicated among multiple venture firms (Lerner, 1994). When this occurs, one firm usually takes the role of the lead for the round and is most actively involved in monitoring the investment. While it is not uncommon for new venture firms to join a syndicate as financing rounds in a company progress, once a firm has joined a syndicate, it is relatively unusual for it to drop out in subsequent rounds.

2.2 Potential mechanisms

Given the structure of venture capital financing just described, the potential mechanisms by which shocks might propagate across sectors would have to be quite different from those at work in the banking context. In particular, it may be necessary for a bank to shrink its balance sheet to meet capital adequacy requirements, after investing heavily in a poor performing sector. To the extent that various forms of runs by short-term liability holders can occur, such runs can amplify these dynamics. In contrast, venture capital firms are neither subject to capital adequacy requirements nor runs, as investors are required to make long-term capital commitments. Indeed, to the extent that venture firms can be thought of as investing self-contained funds of fixed sizes, it is not immediately clear that poor performance in one part of their portfolio should affect continuation financing decisions in another part. There are, however, at least three mechanisms through which this might occur.

First, 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. As a result, such a firm might become more selective about which companies to continue financing across all sectors.

Second, venture capital partnership agreements typically contain capital recycling provisions that allow capital from successful early exits to be reinvested in portfolio companies (Rossa and Tracy, 2007). Because of the annual management fees taken by venture firms, the full amount of capital committed to a fund would not actually be invested absent recycling. Recognizing this, limited partners often allow capital to be recycled up until the point where invested capital equals 100-125% of committed capital. This implies that a negative shock to a particular sector could effectively decrease the size of a fund with high exposure to that sector, as such a fund would likely have less capital from early exits to reinvest.

Third, and 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 fundraising activity from directly affecting existing portfolio companies. However, according to recent survey evidence, nearly half of venture funds lack such restrictions (Rossa and Tracy, 2007). Moreover, even with these restrictions, there remains an indirect channel through which existing portfolio companies can be affected by the fundraising activity of their backers. 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. Just as important, a firm may sustain serious damage to its reputation as a result of having missed out on the latest round of innovations. Thus, 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. Much like in Shleifer and Vishny (1997) then, venture firms would have to abandon profitable positions due to the decreased confidence of their investors.

Finally, it should be noted that there is also a potential countervailing force in this context. The three mechanisms outlined above are all ways in which venture firms with high exposure to a sector that experiences a downturn effectively have fewer resources to put to work, due to their reduced access to the public equity market, as well as their reduced fundraising capacity. Holding resources constant, however, one might expect that a downturn in one sector might actually benefit companies in unrelated sectors, particularly if they are backed by venture firms with high exposure to the depressed sector. This is because equalizing marginal products of investment across their current portfolio, venture firms would tend to increase their allocation to such companies.[1] Thus, for a downturn in one sector to propagate to companies in unrelated

[1] This relates closely to the "bright side" view of internal capital markets. For theoretical work in this area see Williamson (1975); Meyer, Milgrom, and Roberts (1992); Gertner, Scharfstein, and Stein (1994); Stein (1997); Scharfstein and Stein (2000); Rajan, Servaes, and Zingales (2000). For particularly related empirical work see Lang, Ofek, and Stulz (1996); Lamont (1997); Shin and Stulz (1998); Rajan, Servaes, and Zingales (2000); Ozbas and Scharfstein (2010). Indeed, although diversified conglomerates are not generally considered financial intermediaries, venture capital firms do resemble them in some ways. I primarily relate this work to the banking literature, however, due to the informational problems that are important in both the banking and venture capital contexts.

sectors through a venture firm, the decrease in firm resources resulting from the downturn must outweigh the increase in the relative attractiveness of companies unrelated to the downturn.

3 Empirical Strategy

To investigate the propagation of financial shocks in venture capital, I examine continuation financing outcomes for venture-backed companies in non-IT sectors, during the period surrounding the collapse of the technology bubble. In particular, I exploit variation in the degree of a venture firm's exposure to the internet sector. Again, this variation exists largely due to the fact that some firms specialize in non-IT sectors, while others make both IT and non-IT investments. I will sometimes refer to generalist firms with high internet exposure as "internet-focused venture firms." Note, however, that the most highly internet-focused firms will not be included in the analysis, as I only consider firms that also made 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 the effect of having investors in poor financial health due to high internet exposure. A company is thus considered to be in the treatment group if its venture capitalists had high exposure at the peak of the bubble and in the control group if they had low exposure at that time. The before and after periods are defined as the three years preceding and following the peak, respectively. The outcome of interest is the likelihood of a portfolio company receiving a follow-on round of financing. One approach would be to estimate a discrete response model with a dependent variable equaling one if a company, i , considered for continued financing at time t received a follow-on round. Of course, the difficulty with this approach is that, for companies that did not receive a follow-on round, the time t at which they were considered and rejected is unknown. Furthermore, regardless of whether the company was ultimately accepted or rejected for continued financing, it is somewhat unrealistic to think of deliberation over this decision as having taking place at one particular date.

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

$$h_{ijt}(\tau) = h_0(\tau)\exp(\beta_1 After_t + \beta_2 InternetVC_{ij} + \beta_3 After_t \times InternetVC_{ij} + \boldsymbol{\delta}'\boldsymbol{x}_{ijt}), \qquad (1)$$

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 $InternetVC_{ij}$ and $After_t$ are the treatment and after indicators, respectively, while $\boldsymbol{x_{ijt}}$ represents a vector of controls. Using the language of survival analysis, a spell is defined at the company-round level and an event is defined as the raising of a follow-on round. The outcome being modeled, $h_{ijt}(\tau)$, is continuation hazard as a function of analysis time, conditional on covariates. To be more precise, the hazard function is the limiting probability that an event occurs in a given time interval (conditional upon it not having occurred yet at the beginning of that interval) divided by the width of the interval:

$$h(\tau) = \lim_{\triangle\tau \to 0} \frac{\Pr(\tau + \Delta\tau > T > \tau | T > \tau)}{\Delta\tau}, \qquad (2)$$

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

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

$$h_{ijt}(\tau) = h_0(\tau) \exp(\beta_1 + \beta_2), \tag{3}$$

but the actual expected hazard is,

$$h_{ijt}(\tau \mid InternetVC_{ij} = 1, After_t = 1) = h_0(\tau) \exp(\beta_1 + \beta_2 + \beta_3). \tag{4}$$

The percent change in expected hazard due to treatment, $exp(\beta_3) - 1$, can be thought of as analogous to the normal difference-in-differences estimator. If internet-focused venture firms became troubled in the post-bubble period and were more selective about making disbursements to portfolio companies as a result, one would expect this coefficient to be negative. Of course, treatment here is not actually binary. The extent of a venture firm's exposure to the internet sector is in fact continuous. Recognizing this, I also estimate the above model replacing the binary treatment variable $InternetVC_{ij}$ with the continuous variable upon which it is based $InternetExposure_{ij}$. I also estimate the model replacing the binary variable $After_t$ with the continuous variable $log(InternetFlows_t)$, which represents aggregate flows to internet funds during the quarter corresponding to time t. The details concerning the construction of these variables will be discussed in greater detail in the next section.

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

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

Perhaps the most obvious potential candidate for such a characteristic is geography. For example, if venture firms with high internet exposure tended to be located in Silicon Valley and invested in portfolio companies near their headquarters, it may be that their non-IT portfolio companies suffered a greater decline due to the decline in the local economy. To address this concern, I include fixed effects for 13 regions (including Northern California) as well as interactions between these fixed effects and the $After_t$ indicator variable, to control for the fact that companies in different regions might have felt differential effects of the collapse of the technology bubble. Similarly, I include a full set of fixed effects for the sector and stage of development of the portfolio company as well as interactions between those fixed effects and the $After_t$ 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 limit attention to follow-on rounds that were successfully raised. Presumably, companies that succeeded in obtaining continuation financing after the bubble burst were less likely to have unobservable characteristics that made them worse investments during that time. For each round, I observed whether investors from the previous round of the company failed to participate. As mentioned earlier, it is relatively uncommon for venture firms to drop out of rounds in this manner under ordinary circumstances. I then examine whether venture firms with greater internet exposure had a greater increase (from before to after the peak of the bubble) in their probability of dropping out of a round. If internet-focused venture firms became less likely to participate even in rounds deemed by others to have been merited, this would provide further evidence that these venture firms became more selective as a result of poor health. If this were found, however, it would also suggest that some companies were able to overcome non-participation from previous venture capital investors, although likely not enough to eliminate the overall negative effect of internet exposure. Indeed, due to the informational problems described earlier, it is likely that only the best companies would have been able to raise follow-on rounds without previous investors. If so, many other companies that deserved continued financing would have been unable to obtain it, due to their affiliation with internet-focused venture firms.

4 Data

4.1 Key measures

The data used in this study come from the private equity portion of the Thomson-Reuters ThomsonOne database.[2] ThomsonOne has data both on 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) as well as venture firm fundraising (including the size and close date of all funds raised by a firm). I restrict the sample to venture capital financing rounds involving U.S. companies operating in non-IT sectors. I also include only rounds that were backed by venture capital organizations structured as autonomous partnerships. That is, rounds backed entirely by individuals or entities such as corporate-sponsored venture funds are omitted. The estimation window runs from March 31, 1997 to March 31, 2003. Note that some spells (rounds) 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. A related problem arises due to spells with unknown end dates. After a company has an IPO, is acquired, or goes defunct it should leave the risk pool. In some cases, however, particularly for companies that ultimately went defunct, the date at which the company ceased to be at risk of continued financing is not recorded in the data. In these cases, I censor the spells at one year after the last observed financing round.

[2]Before being incorporated into the ThomsonOne database these data were previously available from VentureEconomics.

Another issue with the data, previously reported by Lerner (1995), is that some companies appear to have too many financing rounds reported. This is likely due to staggered disbursements from a single round being misreported as multiple rounds. Also, a small number of companies have consecutive rounds of financing that are extremely far apart. I thus restrict the sample to companies with rounds no less than 30 days and no more than 6 years apart. Results change little, however, if these companies are included.

The post-bubble period, in which the $After_t$ 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 alongside quarterly flows to venture capital funds. Internet stock returns are calculated following 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. As Greenwood and Nagel explain, this methodology is used because SIC codes fail to identify the bubble segment of the market in many cases.[3] Quarterly flows to newly raised venture capital funds are obtained from the ThomsonOne database. The aggregate series is shown as well as flows to internet-specific funds, as categorized by Thompson-Reuters. Note that internet-specific fund flows do not fully reflect the amount of money raised by venture capital firms for internet investments, as many funds made substantial internet investments but did not market themselves as internet-specific funds. Commitments are converted to real 2000 dollars using the GDP deflator. The dotted vertical line in the figure corresponds to March 31, 2000, which is the peak of all three series. Thus, not only did internet stocks peak at this date, but so did venture capital fundraising. The estimation window is chosen accordingly to run from three years prior to the peak to three years following the peak. The results that will be presented change little, however, if the definition of the peak is moved forward or backward several months. In addition, some specifications will use the quarterly internet fund flows variable directly, which avoids the need to define before and after periods.

The degree of a venture capital firm k's exposure to internet investments, $InternetExposure_k$, is measured as the percent of the total amount invested by the firm that was invested in companies

[3]For example, the internet stock eBay has SIC code 738, which places it in the Business Services industry.

operating in the internet sector, during the ten years leading up to the peak. A ten year window is chosen, as this is the life of a typical venture fund. Results are similar, however, if a five year window is used. To limit the effect of outliers that may occur due to firms with few investments in the data, firms with less than five observed investments during this period are considered to have unknown internet exposure.

Note that this measure of internet exposure includes investments in companies that went public, were acquired, or went defunct prior to the peak. An alternative strategy would be to look only at a firm's active portfolio as of March 31, 2000 to determine its internet exposure. Trying to isolate active portfolio companies at the peak, however, is somewhat complicated again by the fact that the date of failure for defunct companies is usually unknown. Another complication is that lockup provisions typically restrict venture firms from selling their shares for some period of time following an IPO. In any case, it is not clear that this is conceptually the measure of interest here, as even if a venture firm did not hold many active internet companies in its portfolio at the peak of the bubble, if it was perceived as an internet specialist due to its investment history, it would likely have faced difficulty raising a new fund in the post-bubble period nevertheless. Finally, one would expect that firms that invested most heavily in internet companies during the run up were also those that were left with the most internet companies in their active portfolio at the peak, so these two measures would likely be very highly correlated.

As mentioned before, funding rounds are often financed by syndicates of multiple venture firms. 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 venture firm 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 backer were in trouble, even if that backer 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 who has invested in the company the longest, following Gompers (1996). Ties are broken by the total amount invested in the company, inclusive of the current round.

Using this definition, a lead venture firm cannot be uniquely identified in some cases and is then simply considered to be unknown.

4.2 Summary statistics

After the sample restrictions described above are imposed, I am left with observations on 797 venture firms, funding 7,470 rounds of 3,947 companies. Table 1 shows the composition of the sample both in terms of companies and rounds. These differ as the average company in the sample received nearly two rounds of financing. Rounds are the relevant unit of observation in most of the analysis to follow in the next section. Panel A breaks down the sample by region. The region with the greatest amount of venture activity, both in terms of companies and rounds, is Northern California. This is closely followed by Southern California, New York, and New England. In the final four columns of the table, the regional composition of the sample is also shown for rounds backed by syndicates in the extreme quartiles of internet exposure. As speculated earlier, rounds backed by venture firms in the top quartile of internet exposure ($InternetVC_{ij} = 1$) are much more likely to be associated with portfolio companies located in Northern California than are rounds in the bottom quartile ($InternetVC_{ij} = 0$).

Panel B shows the breakdown of companies by sector. Life sciences companies operating in the medical/health and biotechnology sectors account for over half of the observed financing rounds. After this, the consumer related and industrial/energy sectors are the most prevalent. Further dividing the sample again by $InternetVC_{ij}$ shows that rounds backed by venture firms with high internet exposure were more likely to be in the consumer related and business services sectors. Note that the consumer related category refers to non-IT consumer related companies such as those operating in the food and beverage sector. Thomson-Reuters reserves separate categories for IT-related consumer products such as computer hardware and software.

Finally, Panel C breaks the sample down by stage. In this case, only the round level is shown, as companies change stages from round to round. The order of the stages from least developed to most are: seed, early, expansion, later, and acquisition/public. By far the most common stage financed is the expansion stage with slightly over 40% of observed rounds occurring at this stage. This is followed by early, later, acquisition/public and finally seed stage rounds. Seed stage rounds may be the most rare because this stage is often financed by individuals. In addition, companies are likely to progress from the seed stage rapidly, whereas they may stay in the expansion stage for several rounds. Rounds financed by internet-focused venture firms tended to be concentrated somewhat more in early stage companies and less in acquisition/public stage companies.

Summary statistics of the key variables used in the analysis are presented in Table 2. These statistics are presented with varying units of observation as appropriate. For example, the internet exposure of syndicates backing rounds is shown at the round level. As described earlier, this is measured for the whole syndicate as well as the lead venture firm in the syndicate. When the lead venture firm cannot be uniquely identified, the former may be known while the latter is not. When the round contributions of firms in the syndicate are not recorded in the data, the reverse may be true. Both measures of internet exposure appear to be distributed similarly with a mean of slightly over 18%. Thus, the average round in the sample was backed by venture firms that made 18% of their total disbursements to internet companies in the decade leading up to the peak of the bubble. The mean number of investors in a round was slightly less than three. The distribution of internet exposure is also shown at the venture firm level. The average venture firm had internet exposure of 24%, indicating that lower exposure companies must have funded more rounds in the data. Though not shown in the table, the modal internet exposure in this sample of firms making non-IT investments was zero, with slightly over 20% of firms having no internet investments at all. As stated earlier, internet exposure is based on observed investments in the ten years leading up to the peak. The average firm in the sample had almost 60 observed investments during this period. At the quarter level, summary statistics for flows into venture funds are shown. These are the same series as those depicted in Figure 1, which has already been discussed. The remaining variables in the table will be discussed as they appear in the analysis of the next section.

5 Results

5.1 On average, IT companies affected, non-IT companies unaffected

I begin by verifying that IT companies, and particularly internet companies, had greater difficulty raising continuation financing in the post-bubble period. Were this not the case, it would seem unlikely that non-IT companies backed by internet-focused venture firms would have experienced negative effects from the collapse of the bubble. I estimate univariate Cox models of the form,

$$h_{ijt}(\tau) = h_0(\tau)\exp(\beta_1 After_t), \tag{5}$$

for each IT sector in the data. Results are shown in Panel A of Table 3. Standard errors are clustered by portfolio company. The implied percent change in hazard from before to after the peak, $exp(\beta_1) - 1$, is shown below the raw coefficients. For companies in most of the IT sectors, the hazard of raising a continuation round was considerably lower in the post-bubble period. In particular, companies in the communications, hardware, and software sectors experienced a decrease in hazard of over 20 percent. 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 over 50 percent.

The results for non-IT sectors are shown in Panel B. Companies in non-IT sectors did not, on average, suffer major declines. At conventional level of significance, biotech, consumer, energy, medical and other non-IT companies all had a statistically insignificant change in hazard in the post-bubble period. Moreover, noisy point estimates indicate a less than 10 percent decline in all non-IT sectors except energy, which is estimated to have had a 9 percent increase. This confirms that relative to IT-companies, non-IT companies experienced a much less dramatic change, on average, in their ability to raise continuation rounds in the post-bubble period. Note, however, this is not necessary for identification, given the difference-in-differences approach outlined earlier.

5.2 Non-IT companies backed by internet VCs were affected

Next, I estimate the difference-in-differences specification of Equation 1. The treatment indicator variable, $InternetVC_{ij}$, is set equal to one if $InternetExposure_{ij}$ (for the venture firms backing the jth round of company i) is in the top quartile of all rounds. The treatment indicator is set equal to zero if $InternetExposure_{ij}$ is in the bottom quartile. Rounds in the middle two quartiles are omitted under this specification, because it is difficult to discretely categorize rounds with $InternetExposure_{ij}$ near the median as either treated or untreated. In the analysis to follow, the entire sample will be used along with the continuous measure of internet exposure. In this case, however, I am interested in comparing the experience of companies backed by internet-focused venture firms, with that of those backed by firms with virtually no internet exposure. Referring back to the summary statistics presented in Table 2, the 25th percentile of $InternetExposure_{ij}$ is between 5% and 7%, depending on how the exposure of a syndicate is measured; the 75th percentile is around 26%.

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, following Cameron, Gelbach, and Miller (2006). The estimated percent change in hazard due to treatment, $exp(\beta_3) - 1$, is shown below the raw coefficients. Beginning with the first column, the estimate of β_3 is negative and statistically significant. The magnitude of the coefficient implies a decline in continuation hazard of 34% due to treatment. Thus, the estimated treatment effect is quite substantial. The coefficients on $After_t$ and $InternetVC_{ij}$ are also positive and statistically significant under this specification. This suggests that non-IT companies funded by non-internet syndicates were able to obtain continuation financing more readily in the post-bubble period than previously. It also suggests that relative to other non-IT companies, those backed by internet-focused syndicates had less difficulty raising follow-on rounds before the collapse. Neither of these results, however, turn out to be as robust as the main finding.

Figure 2 illustrates the estimates from the first column graphically. Again, with the proportional hazards assumption the baseline hazard function is left unestimated. However, given the estimated β coefficients, a smoothed baseline hazard function can be backed out. It is useful to examine the shape of this curve to assure that it is reasonable. As speculated earlier, it appears that the hazard function conforms to an inverted "U" shape. The proportional shifts in the baseline hazard, shown at various values of the covariates, simply reflect the estimated coefficients just discussed. The figure shows graphically that non-IT companies backed by internet-focused syndicates experienced a decrease in continuation hazard in the post-bubble period (Panel A), whereas those backed by non-internet syndicates experienced an increase (Panel B). The difference in these differences is the estimated treatment effect.

In the second column of Table 4, company stage, region, and sector fixed effects are added to the specification. With these additional controls, the estimated treatment effect drops to 25%. Also, the effect of the $After_t$ indicator becomes statistically insignificant, while there is little change in the estimated coefficient on $InternetVC_{ij}$. This suggests that the apparent increase in hazard for non-IT companies funded by non-internet firms partly reflected a change in the characteristics of the companies funded by these firms in the post-bubble period. In the third column, I allow interactions between the company controls and the $After_t$ indicator.[4] As previously explained, this is important, as companies with certain characteristics might have been both more adversely affected by the collapse of the bubble and more likely to have been funded by an internet-focused syndicate. After controlling for these interactions, the estimated treatment effect remains large and statistically significant at approximately 22%. Moreover, the small change in the point estimates between columns two and three is comforting in that it suggests that the results in the previous columns were not largely driven by a tendency for internet-focused venture firms to have invested in non-IT companies with observable characteristics that made them worse investments after the bubble. It is still possible that unobserved characteristics of this type are driving the results. This possibility will be addressed shortly.

In columns four through six, I estimate the same specifications as in the first three columns, but defining the variable $InternetVC_{ij}$ based on the internet exposure of only the lead venture firm in the round. This gives rise to similar results overall, with the estimated treatment effect ranging from 36% to 26%.

[4]The most prevalent categories are omitted i.e. Northern California, expansion, and medical/health.

Next, I estimate the same regressions, substituting $InternetExposure_{ij}$ for $InternetVC_{ij}$, and making use of the entire sample. This takes advantage of the fact that treatment is not actually binary in this case but continuous. Results are reported in Table 5. As in the previous set of results, the primary coefficient of interest, β_3, is estimated to be negative and statistically significant. Also as before, estimates of this parameter change little when company controls are interacted with the $After_t$ indicator variable. In fact, the point estimate of β_3 becomes larger in magnitude in moving from column five to column six. To interpret the magnitudes of these estimates, note that the percent change in hazard associated with the end of the bubble is equal to $\exp(\beta_1 + \beta_3 InternetExposure_{ij}) - 1$.[5] Substituting the coefficients estimated in the first column, this expression evaluates to -13.1% for a portfolio company backed by venture firms with mean internet exposure (of 24.3%). For a portfolio company backed by venture firms with $InternetExposure_{ij}$ one standard deviation above the mean (47.8%), the collapse of the bubble was associated with a -33.1% change, or a 20% larger decrease in hazard. In the remaining specifications, this difference is similar, ranging from 14.7% in column five to 18.6% in column four. So again, the magnitude of the estimated effect is substantial.

I also estimate these equations once more, substituting $\log(InternetFlows_t)$ for $After_t$, where $\log(InternetFlows_t)$ represents the log of all flows to internet-specific venture capital funds raised in the quarter corresponding to time t. Thus, instead of defining discrete before and after periods, this specification takes advantage of the continuous variation over time in the perceived prospects of young internet companies, as reflected by flows into internet-specific venture funds. Results are reported in Table 6, with standard errors now clustered also by quarter. Across all six specifications there is an estimated positive and statistically significant interaction between $\log(InternetFlows_t)$ and $InternetExposure_{ij}$, providing evidence that non-IT companies backed by venture firms with greater internet exposure were more sensitive to fluctuations in the internet sector. Note that β_1 is also statistically insignificant across all six specifications, which suggests that non-IT companies backed by venture firms with no internet exposure were not sensitive at all to these fluctuations. The estimated coefficients in the first column imply that as flows to internet

[5] Except in the specifications estimated in columns three and six, which allow for further interactions between company characteristics and $After_t$.

funds dropped from the second quarter of 2000 to the second quarter of 2001, continuation hazard declined by 8.6% for a company backed by venture firms with mean internet exposure and 15.6% for a company backed by firms with internet exposure one standard deviation above the mean, a difference of 7%. The magnitudes of the estimated interaction are similar across all six specifications, though somewhat larger when the internet exposure of the lead venture firm is used in columns four through six.

5.3 Continuation hazard did not increase as bubble inflated, decreased as deflated

The results thus far suggest that the decline in a company's continuation hazard when the bubble burst, was greater the greater the internet exposure of its investors. It is not clear, however, whether this greater decline in continuation hazard primarily reflected hazard being "too high" during the bubble period or "too low" during the post-bubble period. Put another way, contagion among portfolio companies may have taken place both on the upside as well as on the downside. In general, it is not possible to distinguish between these two scenarios using a difference-in-differences framework. It is possible, however, to shed some light on this issue using the quarterly internet flows specification. In particular, if contagion occurred on the upside, one would expect continuation hazard to have increased along with $InternetFlows_t$ as the bubble inflated. To test whether this occurred, I re-estimate the specifications of Table 6, now allowing the interaction between internet flows and venture firm internet exposure to differ before and after the peak of the bubble. Results are reported in Table 7. In all specifications the estimated interaction in the before period is negative and statistically insignificant. This suggests that, as the bubble inflated, non-IT portfolio companies did not become more likely to receive follow-on rounds, even if their venture firm was heavily invested in the internet sector. By contrast, the estimated interaction in the after period is positive and statistically significant across all specifications. This suggests that, as the bubble deflated, portfolio companies did become less likely to receive follow-on rounds, particularly if their venture firm was heavily invested in the internet sector. On the whole, these results provide evidence that contagion among portfolio companies primarily occurred on the downside.

5.4 Internet VCs became more likely to drop out of rounds after collapse

It still remains possible that non-IT companies backed by internet-focused venture firms differed from others along some unobserved dimension that made them worse investments in the post-bubble period. In this case, these companies may have had more difficulty raising continuation funding, not because their investors were experiencing difficulties, but because their future prospects deteriorated alongside those of internet companies. Under this scenario, however, conditional on a continuation round being raised, there would be no reason to expect previous investors with high internet exposure to have a greater increase in their probability of dropping out of the round. If internet-focused venture firms became less likely to participate, even in rounds deemed by others to have been merited, this would suggest that these firms indeed became more selective as a result of poor financial health.

To conduct this falsification test, I estimate probit models of the form,

$$\begin{aligned}\Pr(VCDropout_{ijkt}) = \Phi(&\beta_0 + \beta_1 After_t + \beta_2 InternetExposure_k \\ &+ \beta_3 After_t \times InternetExposure_k + \boldsymbol{\delta}'\boldsymbol{x}_{ijt}). \quad (6)\end{aligned}$$

Observations in this case are at the company-round-VC level. That is, 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, $VCDropout_{ijkt}$ is equal to zero; otherwise, $VCDropout_{ijkt}$ is equal to one. One exception to this rule is made if the venture firm is observed participating again in subsequent rounds of the company. Then the firm is considered a participant in the current round, as its omission is taken to be a data error. 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 8 reports the results, with marginal effects shown alongside the raw coefficients. As $InternetExposure_k$ only varies at the venture firm level, standard errors are clustered accordingly by venture firm as well as portfolio company, again following Cameron, Gelbach, and Miller

(2006). In all three specifications, the estimates of β_1 and β_2 are statistically insignificant while the estimates of β_3 are positive and statistically significant. The coefficients in the first column imply that a venture firm with mean internet exposure had a 1.9% increase in the probability of dropping out of a round, while a firm with internet exposure one standard deviation above the mean had a 4.2% increase, a difference of 2.3%. In the second and third column this difference is 3.2% and 2.9%, respectively. Considering that the unconditional probability of a firm dropping out in the before period was only 10.7%, these magnitudes are again economically meaningful, as they represent a 21.5-29.9 percentage increase. Thus, when companies previously financed by internet-focused firms did raise follow-on rounds, they were less likely to do so with the participation of their previous investors. This would seem most consistent with the hypothesis that internet-focused firms faced difficulties in the post-bubble period and became more selective as a result.

5.5 Internet VCs had increased fundraising difficulty after collapse

Next, I examine further the nature of these difficulties. As discussed earlier, it is likely that venture firms with internet-heavy portfolios had trouble raising new funds from limited partners after the bubble burst. To investigate this, I estimate the same hazard models as before, but now at the venture firm level. Specifically, rather than estimating the hazard of a portfolio company raising a continuation round from venture firms, I now estimate the hazard of a venture firm raising a follow-on fund from limited partners. In the three columns of Table 9, I repeat the three specifications of Tables 4 through 6 at the venture firm level. Standard errors are clustered by venture firm, and also by quarter in the third column.

The same general pattern emerges as did at the portfolio company level. The coefficients on the interaction terms $After_t \times InternetVC_k$ and $After_t \times InternetExposure_k$ are both estimated to be negative, while the coefficient on $\log(InternetFlows_t) \times InternetExposure_k$ is estimated to be positive; all are statistically significant. This suggests that the adverse effect of the collapse of the technology bubble on fundraising was greater for venture firms that were more associated with internet investing. Also, the coefficients on $InternetVC_k$ and $InternetExposure_k$ are estimated to be positive in columns one and two, suggesting that internet-focused firms, which experienced increased fundraising difficulty in the post-bubble period, also found it easier to raise funds during the bubble. The magnitudes of these estimates are again substantial. The coefficients in the first column imply that venture firms in the top quartile of internet exposure had a 47.7% larger decrease in fundraising hazard than those in the bottom quartile. The estimates in the second column imply that, for an average venture firm, a one standard deviation increase in internet exposure was associated with a 12.54% larger decline in fundraising hazard. Finally, the estimates in the third column imply that the same change in internet exposure was associated with a 9.2% larger decline in fundraising hazard as quarterly flows to internet funds dropped from the second quarter of 2000 to the second quarter of 2001.

5.6 Companies backed by young VCs late in fundraising cycle were most affected

Thus, internet-focused venture firms faced increased difficulty in raising new funds after the collapse of the bubble. Also, at the same time, non-IT companies funded by these firms had increased difficulty in obtaining continuation financing in the post-bubble period. While these two facts would appear connected, little evidence has yet been presented to directly establish such a connection. If portfolio companies associated with internet-focused venture firms were indeed less able to raise follow-on rounds due to the diminished fundraising capacity of their investors, one would expect the negative effect of venture firm 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 more likely be running low on uninvested capital and therefore be concerned about a decline in their fundraising capacity.

To test this, I re-estimate the specifications of Table 5, now allowing all of the primary variables to interact with $YearsSinceRaised_{ijt}$, a variable representing the number of years (as of time t) since the venture firms backing the jth round of company i last raised a fund. As with internet exposure, $YearsSinceRaised_{ijt}$ is defined as 1) the mean of $YearsSinceRaised_{kt}$ for all venture firms participating in the round, weighted by their contribution to the round and 2) the value of $YearsSinceRaised_{kt}$ for the lead venture firm in the round. In addition to these interactions, I also include an additional set of controls for $After_t \times InternetExposure_{ij} \times Stage_{ij}$ 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.[6]

Results are reported in Table 10. The primary coefficient of interest is that on the triple interaction term $After_t \times InternetExposure_{ij} \times YearsSinceRaised_{ijt}$, which is estimated to be negative and statistically significant across all specifications. This suggests that the negative effect of the bubble's collapse on portfolio companies backed by high internet exposure firms was greater the longer it had been since those firms raised a new fund. Also note that the estimated coefficient on the double interaction $After_t \times InternetExposure_{ij}$ 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. In the first three columns, the coefficient on $YearsSinceRaised_{ijt}$ is also estimated to be negative and statistically significant, suggesting that even before the bubble burst, portfolio companies backed by venture firms running late in their fundraising cycle were less likely to raise follow-on rounds. However, when $YearsSinceRaised_{ijt}$ is defined at the lead firm level this coefficient becomes insignificant. In either case, the effect of $YearsSinceRaised_{ijt}$ appears to have been much stronger in the post-bubble period and particularly for companies backed by venture firms with high exposure to the internet sector. Again, this is consistent with the hypothesis that such venture firms became more selective in funding companies across all sectors as their capital reserves dwindled and they anticipated difficulty raising new funds from limited partners, due to their recent investment history.

A venture firm's recent investment history would likely affect its fundraising less if the firm had a long investment track record. This would occur, for example, if limited partners updated their beliefs about a firm's investment ability in a Bayesian manner. Consistent with this, many well-established firms, including Kleiner Perkins, Charles River Ventures, and Accel Partners, returned capital to limited partners after the collapse, citing reduced investment opportunities. Such behavior would certainly seem to indicate that these firms were confident in their ability to

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

raise future funds. Young venture firms, on the other hand, were likely less confident. Thus, if companies backed by young firms were more affected by the internet exposure of their investors, this would provide further evidence that venture firm fundraising difficulties were indeed driving the baseline results presented earlier.

I therefore re-estimate the specifications of the previous table, now allowing all the primary variables to further interact with $YoungVC_{ij}$, an indicator variable equaling one if the lead venture firm in the round was less than six years old at the peak of the bubble and zero otherwise. For expositional clarity, I present the results for the $YoungVC_{ij} = 1$ and $YoungVC_{ij} = 0$ subgroups separately, as this avoids quadruple interaction terms.[7] Results are presented in Table 11. The primary coefficient of interest is again that on the triple interaction term $After_t \times InternetExposure_{ij} \times YearsSinceRaised_{ijt}$. In the first three columns, this coefficient is estimated to be negative and statistically significant for the $YoungVC_{ij} = 1$ subgroup. In the final three columns, it is estimated to be smaller in magnitude and statistically insignificant (or marginally significant) for the $YoungVC_{ij} = 0$ subgroup. Most importantly, the difference in this coefficient for the two subgroups is large and statistically significant. Therefore, the portfolio companies that experienced the largest decline in continuation hazard when the technology bubble burst, were those backed by venture firms that 1) had high internet exposure, 2) had not raised a fund recently, and 3) had a short investment track record. Again, these results are consistent with the venture firm fundraising mechanism.

5.7 Companies backed by internet VCs were no less productive prior to collapse

Much of the discussion 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 this possibility is distinct from the endogeneity concerns discussed earlier, as those centered around the notion that non-IT companies funded by venture firms with high internet exposure might have

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

had unobservable characteristics that caused their prospects to decline alongside those of internet companies. Under the endogeneity scenario, the decline in continuation hazard suffered by these companies might wrongly be attributed to the declining health of their investors. Evidence against this has already been presented. It could be, however, that the estimated decline in continuation hazard experienced by these companies was indeed attributable to the health of their financiers, and yet this decline was not entirely inefficient. This would be the case if internet-focused venture firms anticipated high returns on their internet holdings and took chances on bad (even negative NPV) non-IT investments as a result. This would in some ways be akin to the agency costs of free cash flows posited by 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, as they might have perceived a larger opportunity cost in doing so.

To shed light on this issue, I examine whether companies with 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/heath sectors, where patents play a crucial role. I obtain patent data from the National Bureau of Economic Research (NBER) Patent Data Project (Hall, Jaffe, and Trajtenberg, 2001). These data are then matched with the Thomson-Reuters data on company name, using name standardization and matching procedures developed by the NBER Patent Data Project. [8] Matches are then confirmed manually. Using these procedures, I am able to match 36% of the companies in the sample. I then limit the sample to companies that raised their first round of financing in the three years prior to the peak of the bubble (March 31, 1997 to March 31, 2000). For each company, I calculate the total number of successful patents applied for before the collapse. Also, for each of these patents, I calculate the total number of citations received during the three years following the date the patent was granted. This is in keeping with a large patenting literature that uses citations as a proxy for economic importance (Jaffe and Trajtenberg, 2002). As in Lerner, Sorensen, and Strömberg (2008), citations are only counted for a three year window, so

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

that earlier patents do not have greater time to garner citations.[9]

Because both total patents and citations are count variables, some form of count regression model is called for. The most widely used models in this class are the Poisson and negative binomial models. Both assume that the probability distribution of the count variable depends on an intensity parameter, λ, which itself is modeled as a function of covariates: $\ln(\lambda_i) = \mathbf{x_i'}\beta$. The negative binomial model can be viewed as a generalization of the Poisson model, which allows for overdispersion. As unreported tests strongly reject the null of equidispersion in this case, I estimate negative binomial models of the form,

$$\lambda_i = exp(\beta_0 + \beta_1 InternetExposure_i + \boldsymbol{\delta}'\boldsymbol{x}_i). \tag{7}$$

In this case, the variable $InternetExposure_i$ represents the internet exposure of the venture firms that backed the first round of a portfolio company. When total patents are the outcome of interest, i indexes portfolio companies; when citations are the outcome of interest, i indexes individual patents.

Results are reported in Table 12 with coefficients reported in terms of mean marginal effects to ease interpretation. In columns one and three, i indexes portfolio companies and λ_i represents company patenting intensity.[10] In both columns the coefficient on $InternetExposure_i$ is estimated to be positive and statistically insignificant. Thus, I fail to reject the null that the number of patents a company issued before the collapse of the bubble and the internet exposure of its investors were unrelated.

It is still possible that the ideas patented by non-IT companies backed by internet-focused firms tended to be less economically important. This is investigated in columns two and four, where λ_i represents patent citation intensity. It is well known that citation intensity varies widely

[9] Due to the lag between the date patents are applied for and the date they are granted, a small number of patents applied for between March 31, 1997 and March 31, 2000 are granted after December 31, 2003. This means that they have less than three years to receive citations before the end of 2006, when the NBER citation data end. These patents are therefore dropped in the citation analysis.

[10] In this analysis, companies differ in terms of their exposure time (i.e. the time they had available to apply for patents before the peak of the bubble) due to the fact that they were founded at different dates. This is adjusted for by altering the log likelihood function appropriately (Cameron and Trivedi, 1998), assuming exposure time to be the number of days between the first financing round and March 31, 2000.

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.[11] The variable $\ln(\gamma_i)$ is then included in the model with its coefficient constrained to one to convert citation intensity into relative terms, as in Lerner, Sorensen, and Strömberg (2008). In both columns two and four, the coefficient on $InternetExposure_i$ is again estimated to be positive and statistically insignificant. Thus, I also fail to reject the null that the number of citations a company's patents received and the internet exposure of its investors were unrelated. Therefore, while patent productivity is by no means a perfect measure of company performance, there is no evidence from this standpoint to suggest that non-IT companies funded by internet-focused firms tended to be of lower quality.

6 Conclusion

While intermediaries serve an important function in financial markets by monitoring opaque investments, the private information that they accumulate can lead their clients to become locked-in. As a result, intermediary clients can be hurt when their intermediary suffers an adverse shock from unrelated investments.

In this paper I study 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, internet-focused venture firms were more likely to drop out of financing rounds, even when those rounds were deemed by others to have been merited. Exploring the mechanism underlying these results, I find that internet-focused venture firms suffered a larger decline in their fundraising capacity during this period, which may have been transmitted to their portfolio companies. Consistent with this, I estimate that the negative effect of a venture firm's internet

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

exposure on its portfolio companies was strongest for young venture firms that had not raised a new fund recently. Finally, examining patent productivity before the collapse of the bubble, I find no evidence that non-IT companies backed by internet-focused venture firms were of lower quality.

This paper adds to our understanding of the downsides of financial intermediation. The venture capital industry has played a vital role in financing young innovative companies and thus merits close attention. Moreover, there are many reasons to think that intermediary health would be of particular importance for venture-backed companies. Overall, the results found here indicate that despite the long-term structure of venture capital partnership agreements, the financial health of venture firms still fluctuates with market conditions. These fluctuations can lead to significant distortions in continuation financing decisions that ultimately determine whether portfolio companies survive.

References

Admati, Anat R., and Paul Pfleiderer, 1994, Robust financial contracting and the role of venture capitalists, *The Journal of Finance* 49, 371–402.

Ashcraft, Adam B., 2006, New evidence on the lending channel, *Journal of Money, Credit & Banking* 38, 751–775.

Bae, Kee-Hong, Jun-Koo Kang, and Chan-Woo Lim, 2002, The value of durable bank relationships: Evidence from korean banking shocks, *Journal of Financial Economics* 64, 181–214.

Baker, Malcolm, and Paul A. Gompers, 2003, The determinants of board structure at the initial public offering, *The Journal of Law and Economics* 46, 569–598.

Bernanke, Ben S., 1983, Nonmonetary effects of the financial crisis in the propagation of the great depression, *The American Economic Review* 73, 257–276.

———, and Alan S. Blinder, 1992, The federal funds rate and the channels of monetary transmission, *The American Economic Review* 82, 901–921.

Brunnermeier, Markus K., and Stefan Nagel, 2004, Hedge funds and the technology bubble, *The Journal of Finance* 59, 2013–2040.

Cameron, A. Colin, Jonah B. Gelbach, and Douglas L. Miller, 2006, Robust inference with Multi-Way clustering, *Working Paper*.

Cameron, A. Colin, and Pravin K. Trivedi, 1998, *Regression Analysis of Count Data* (Cambridge University Press: Cambridge, UK).

Chava, Sudheer, and Amiyatosh K. Purnanandam, 2009, The effect of banking crisis on Bank-Dependent borrowers, *Working Paper*.

Djankov, Simeon, Jan Jindra, and Leora F. Klapper, 2005, Corporate valuation and the resolution of bank insolvency in east asia, *Journal of Banking & Finance* 29, 2095–2118.

Gan, Jie, 2007, The real effects of asset market bubbles: Loan- and Firm-Level evidence of a lending channel., *Review of Financial Studies* 20, 1941–1973.

Gertler, Mark, and Simon Gilchrist, 1994, Monetary policy, business cycles, and the behavior of small manufacturing firms, *The Quarterly Journal of Economics* 109, 309–340.

Gertner, Robert H., David S. Scharfstein, and Jeremy C. Stein, 1994, Internal versus external capital markets, *The Quarterly Journal of Economics* 109, 1211–1230.

Gibson, Michael S., 1995, Can bank health affect investment? evidence from japan, *The Journal of Business* 68, 281–308.

Gompers, Paul, Anna Kovner, and Josh Lerner, 2009, Specialization and success: Evidence from venture capital, *Journal of Economics & Management Strategy* 18, 817–844.

Gompers, Paul A., 1995, Optimal investment, monitoring, and the staging of venture capital, *The Journal of Finance* 50, 1461–1489.

———, 1996, Grandstanding in the venture capital industry, *Journal of Financial Economics* 42, 133–156.

———, and Josh Lerner, 2000, Money chasing deals? the impact of fund inflows on private equity valuation, *Journal of Financial Economics* 55, 281–325.

Greenwood, Robin, and Stefan Nagel, 2009, Inexperienced investors and bubbles, *Journal of Financial Economics* 93, 239–258.

Hall, Bronwyn, Adam Jaffe, and Manuel Trajtenberg, 2001, The NBER patent citations data file: Lessons, insights and methodological tools, *Working Paper*.

Hellmann, Thomas, and Manju Puri, 2000, The interaction between product market and financing strategy: The role of venture capital, *The Review of Financial Studies* 13, 959–984.

———, 2002, Venture capital and the professionalization of Start-Up firms: Empirical evidence, *The Journal of Finance* 57, 169–197.

Hsu, David H., 2004, What do entrepreneurs pay for venture capital affiliation?, *The Journal of Finance* 59, 1805–1844.

Jaffe, Adam B, and Manuel Trajtenberg, 2002, *Patents, Citations, and Innovations: A Window on the Knowledge Economy* (MIT Press: Cambridge, MA).

Jensen, Michael C., 1986, Agency costs of free cash flow, corporate finance, and takeovers, *The American Economic Review* 76, 323–329.

Jiménez, Gabriel, Steven Ongena, José-Luis Pedró, and Jesús Saurina, 2010, Credit availability: Identifying Balance-Sheet channels with loan applications, *Working Paper*.

Kang, Jun-Koo, and René M. Stulz, 2000, Do banking shocks affect borrowing firm performance? an analysis of the japanese experience, *The Journal of Business* 73, 1–23.

Kaplan, Steven N., and Josh Lerner, 2010, It ain't broke: The past, present, and future of venture capital., *Journal of Applied Corporate Finance* 22, 36–47.

Kaplan, Steven N., and Antoinette Schoar, 2005, Private equity performance: Returns, persistence, and capital flows, *The Journal of Finance* 60, 1791–1823.

Kaplan, Steven N., and Per Strömberg, 2003, Financial contracting theory meets the real world: An empirical analysis of venture capital contracts, *Review of Economic Studies* 70, 281–315.

———, 2004, Characteristics, contracts, and actions: Evidence from venture capitalist analyses, *The Journal of Finance* 59, 2177–2210.

Kashyap, Anil K., Owen A. Lamont, and Jeremy C. Stein, 1994, Credit conditions and the cyclical behavior of inventories, *The Quarterly Journal of Economics* 109, 565–592.

Kashyap, Anil K, and Jeremy C. Stein, 2000, What do a million observations on banks say about the transmission of monetary policy?, *The American Economic Review* 90, 407–428.

Kashyap, Anil K., Jeremy C. Stein, and David W. Wilcox, 1993, Monetary policy and credit conditions: Evidence from the composition of external finance, *The American Economic Review* 83, 78–98.

Khwaja, Asim Ijaz, and Atif Mian, 2008, Tracing the impact of bank liquidity shocks: Evidence from an emerging market, *American Economic Review* 98, 1413–1442.

Kishan, Ruby P., and Timothy P. Opiela, 2000, Bank size, bank capital, and the bank lending channel, *Journal of Money, Credit and Banking* 32, 121–141.

Lamont, Owen, 1997, Cash flow and investment: Evidence from internal capital markets, *The Journal of Finance* 52, 83–109.

Lang, Larry, Eli Ofek, and René M. Stulz, 1996, Leverage, investment, and firm growth, *Journal of Financial Economics* 40, 3–29.

Lerner, Josh, 1994, The syndication of venture capital investments, *Financial Management* 23, 16–27.

——— , 1995, Venture capitalists and the oversight of private firms, *The Journal of Finance* 50, 301–318.

——— , Morten Sorensen, and Per Strömberg, 2008, Private equity and Long-Run investment: The case of innovation, *Working Paper*.

Meyer, Margaret, Paul Milgrom, and John Roberts, 1992, Organizational prospects, influence costs, and ownership changes, *Journal of Economics & Management Strategy* 1, 9–35.

Ongena, Steven, David C. Smith, and Dag Michalsen, 2003, Firms and their distressed banks: lessons from the norwegian banking crisis, *Journal of Financial Economics* 67, 81–112.

Ozbas, Oguzhan, and David S. Scharfstein, 2010, Evidence on the dark side of internal capital markets, *Review of Financial Studies* 23, 581 –599.

Paravisini, Daniel, 2008, Local bank financial constraints and firm access to external finance, *The Journal of Finance* 63, 2161–2193.

Peek, Joe, and Eric Rosengren, 1995, The capital crunch: Neither a borrower nor a lender be, *Journal of Money, Credit and Banking* 27, 625–638.

Peek, Joe, and Eric S. Rosengren, 1997, The international transmission of financial shocks: The case of japan, *The American Economic Review* 87, 495–505.

——— , 2000, Collateral damage: Effects of the japanese bank crisis on real activity in the united states, *The American Economic Review* 90, 30–45.

Popov, Alexander, and Gregory F. Udell, 2010, Cross-Border banking and the international transmission of financial distress during the crisis of 2007-2008, *Working Paper*.

Puri, Manju, Jörg Rocholl, and Sascha Steffen, 2010, Global retail lending in the aftermath of the US financial crisis: Distinguishing between supply and demand effects, *Working Paper*.

Rajan, Raghuram, Henri Servaes, and Luigi Zingales, 2000, The cost of diversity: The diversification discount and inefficient investment, *The Journal of Finance* 55, 35–80.

Rajan, Raghuram G., 1992, Insiders and outsiders: The choice between informed and Arm's-Length debt, *The Journal of Finance* 47, 1367–1400.

Rossa, Jennifer, and Tennille Tracy, 2007, *Private equity partnership terms & conditions.* (Dow, Jones: Wellesley, MA) 5 edn.

Scharfstein, David S., and Jeremy C. Stein, 2000, The dark side of internal capital markets: Divisional Rent-Seeking and inefficient investment, *The Journal of Finance* 55, 2537–2564.

Schnabl, Philipp, 2010, Financial globalization and the transmission of bank liquidity shocks: Evidence from an emerging market, *Working Paper*.

Sharpe, Steven A., 1990, Asymmetric information, bank lending and implicit contracts: A stylized model of customer relationships, *The Journal of Finance* 45, 1069–1087.

Shin, Hyun-Han, and René M. Stulz, 1998, Are internal capital markets efficient?, *Quarterly Journal of Economics* 113, 531–552.

Shleifer, Andrei, and Robert W. Vishny, 1997, The limits of arbitrage., *Journal of Finance* 52, 35–55.

Slovin, Myron B., Marie E. Sushka, and John A. Polonchek, 1993, The value of bank durability: Borrowers as bank stakeholders, *The Journal of Finance* 48, 247–266.

Stein, Jeremy C., 1997, Internal capital markets and the competition for corporate resources, *The Journal of Finance* 52, 111–133.

———, 2002, Information production and capital allocation: Decentralized versus hierarchical firms, *The Journal of Finance* 57, 1891–1921.

Williamson, Oliver E, 1975, *Markets and hierarchies, analysis and antitrust implications : a study in the economics of internal organization* (Free Press: New York).

Yamori, Nobuyoshi, and Akinobu Murakami, 1999, Does bank relationship have an economic value?: The effect of main bank failure on client firms, *Economics Letters* 65, 115–120.

Figure 1

The Technology Bubble and Venture Capital

This figure shows buy-and-hold returns on publicly traded internet stocks as well quarterly flows to venture capital funds. Internet returns are calculated following 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 ThomsonOne. Only flows to U.S. based funds that are structured as independent private partnerships are included. Flows are converted to real 2000 dollars using the GDP deflator. The vertical line corresponds to the peak of all three series and is located at March 31, 2000.

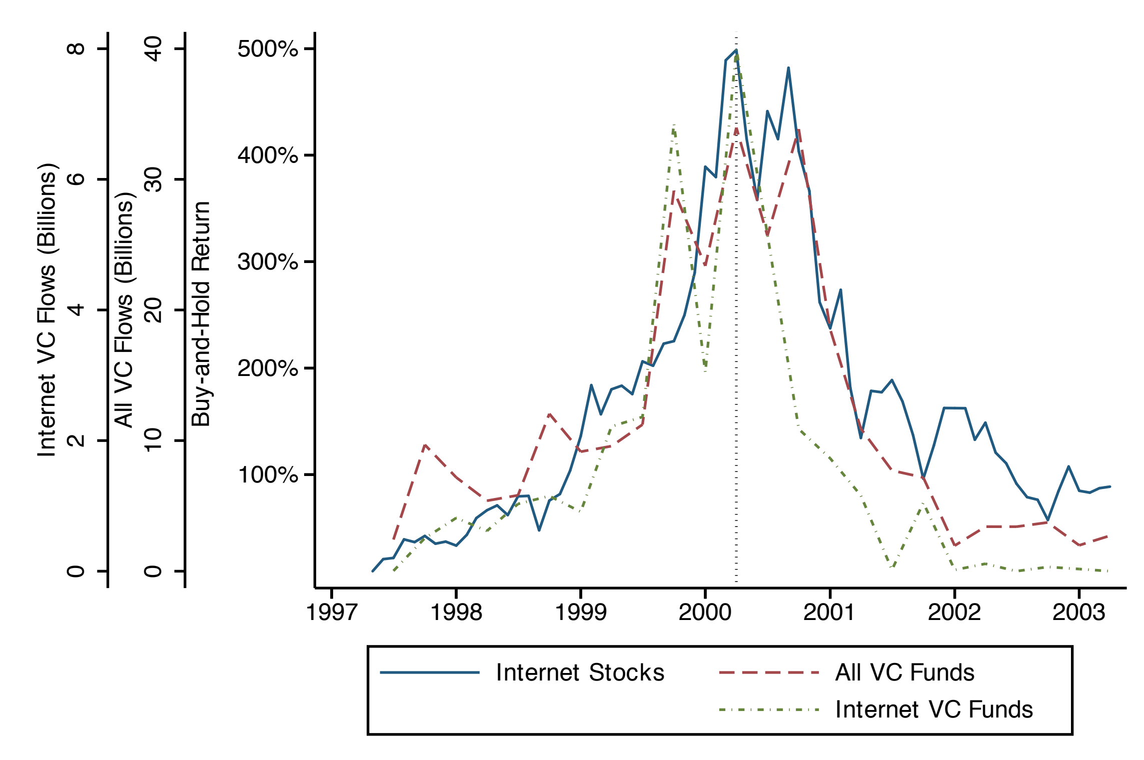
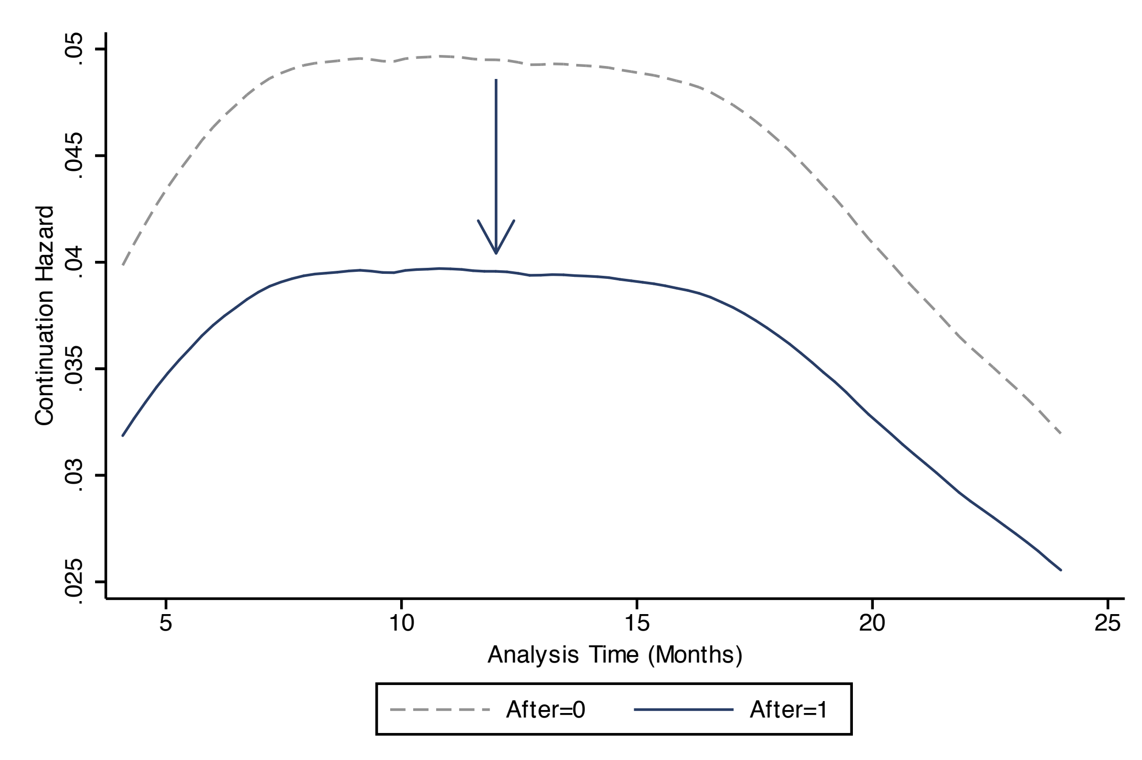


Figure 2
Smoothed Hazard Function

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

(A) **InternetVC=1**



(B) **InternetVC=0**

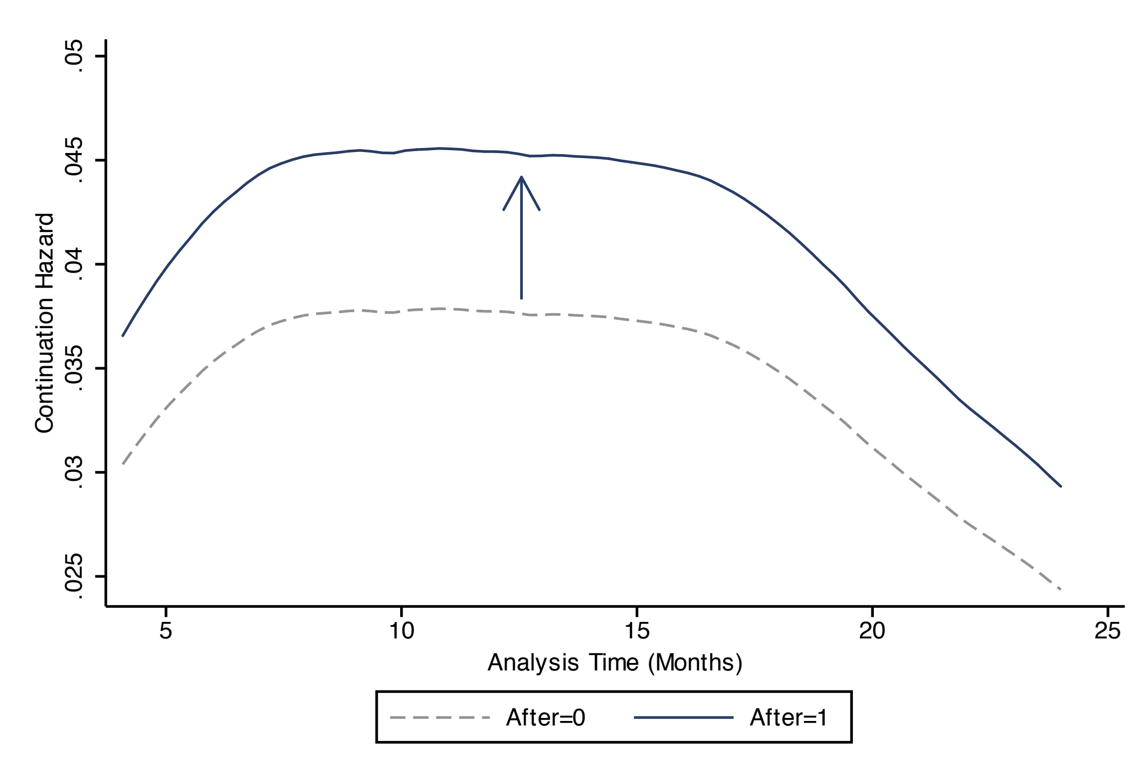


Table 1
Sample Composition

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

	All				Non-Internet VC		Internet VC	
	Companies		Rounds		Rounds		Rounds	
	Freq	Pct	Freq	Pct	Freq	Pct	Freq	Pct
Panel A: Region								
Alaska/Hawaii	5	0.13	8	0.11	0	0.00	5	0.29
Great Lakes	268	6.86	433	5.83	130	7.50	86	5.01
Great Plains	219	5.60	376	5.06	106	6.12	81	4.71
Mid-Atlantic	173	4.43	330	4.44	65	3.75	71	4.13
N. California	537	13.74	1,160	15.61	155	8.94	353	20.55
NY Tri-State	478	12.23	845	11.37	244	14.08	182	10.59
New England	392	10.03	830	11.17	179	10.33	191	11.12
Northwest	118	3.02	258	3.47	56	3.23	51	2.97
Ohio Valley	301	7.70	543	7.31	128	7.39	165	9.60
Rocky Mountains	127	3.25	255	3.43	54	3.12	68	3.96
S. California	440	11.26	920	12.38	214	12.35	212	12.34
South	145	3.71	272	3.66	74	4.27	57	3.32
Southeast	378	9.67	643	8.65	146	8.42	114	6.64
Southwest	327	8.37	557	7.50	182	10.50	82	4.77
Total	3,908	100.00	7,430	100.00	1,733	100.00	1,718	100.00
Panel B: Sector								
Agr/Forestr/Fish	27	0.68	43	0.58	12	0.69	15	0.87
Biotechnology	536	13.58	1,231	16.48	310	17.80	214	12.42
Business Serv.	317	8.03	547	7.32	98	5.63	196	11.38
Construction	57	1.44	84	1.12	27	1.55	20	1.16
Consumer Related	732	18.55	1,208	16.17	260	14.93	355	20.60
Financial Services	305	7.73	432	5.78	116	6.66	130	7.54
Industrial/Energy	480	12.16	745	9.97	227	13.03	139	8.07
Manufact.	193	4.89	263	3.52	69	3.96	59	3.42
Medical/Health	1,090	27.62	2,621	35.09	541	31.06	521	30.24
Other	70	1.77	90	1.20	10	0.57	29	1.68
Transportation	116	2.94	178	2.38	57	3.27	41	2.38
Utilities	24	0.61	28	0.37	15	0.86	4	0.23
Total	3,947	100.00	7,470	100.00	1,742	100.00	1,723	100.00
Panel C: Stage								
Acquisition/Public	-	-	807	10.95	227	13.26	133	7.76
Early Stage	-	-	1,484	20.13	331	19.33	421	24.56
Expansion	-	-	3,100	42.05	751	43.87	751	43.82
Later Stage	-	-	1,252	16.98	215	12.56	220	12.84
Seed	-	-	730	9.90	188	10.98	189	11.03
Total	-	-	7,373	100.00	1,712	100.00	1,714	100.00

Table 2
Summary Statistics

This table shows summary statistics for the key variables used in the analysis. Each variable is shown at the level of observation at which it varies.

	p25	p50	p75	Mean	s.d.	N
Round Level						
Internet Exposure (Whole Syndicate)	0.0698	0.166	0.265	0.186	0.153	6889
Internet Exposure (Lead VC)	0.0512	0.157	0.267	0.182	0.162	6623
Number of Investors	1	2	4	2.806	2.363	7470
VC Level						
Internet Exposure	0.0311	0.192	0.381	0.243	0.235	797
Number of Investments	11	25	61	58.65	99.28	797
Firm Age	2.834	9.251	16.62	10.59	8.918	608
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	0.115	0.319	11823
Company Level						
Total Patents (1997Q2-2000Q2)	0	2	4	3.780	10.67	478
Patent Level						
Number of Citations (First Three Years)	1	4	10	8.607	12.69	1683

Table 3

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

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

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

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 $After_t$ is an indicator equaling one if the date is after the peak of the technology bubble (March 31, 2000) and zero otherwise. Note $After_t$ is a time-varying covariate i.e. it can change in the middle of a spell. The sample is restricted to financing rounds of ventured-backed U.S. companies. The sample period is from March 31, 1997 to March 31, 2003. Raw coefficients are reported. Standard errors are in brackets and are clustered by portfolio company. * and ** denote statistical significance at the 10% and 5% level, respectively.

(A) **IT Sectors**

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

(B) **Non-IT Sectors**

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

Table 4
Non-IT Companies Backed by Internet VCs were Affected: Diff-in-Diffs, Extreme Quartiles

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

$$h_{ijt}(\tau) = h_0(\tau)exp(\beta_1 After_t + \beta_2 InternetVC_{ij} + \beta_3 After_t \times InternetVC_{ij} + \boldsymbol{\delta}'\boldsymbol{x}_{ijt}).$$

Analysis time τ is defined as the time since company i raised its jth round. The variable $After_t$ is an indicator equaling one if the date is after the peak of the technology bubble (March 31, 2000) and zero otherwise. Note $After_t$ is a time-varying covariate i.e. it can change in the middle of a spell. The degree of a venture capital firm k's exposure to internet investments, $InternetExposure_k$, is measured as the percent of the total amount invested by the firm that was invested in companies operating in the internet sector during the ten years leading up to the peak. 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, which is defined to be the one that has invested in the company the longest (ties are broken by cumulative disbursements to the company inclusive of the current round). Based on these measures, the indicator variable $InternetVC_{ij}$ is set equal to one if the syndicate backing the round is in the top quartile of $InternetExposure_{ij}$ and zero if it is in the bottom quartile. The middle two quartiles are dropped. 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 U.S. companies operating in non-IT sectors. The sample period is from March 31, 1997 to March 31, 2003. Raw coefficients are reported. Standard errors are in brackets and are clustered by portfolio company in the first three columns as well as lead venture firm in the final three columns, following Cameron, Gelbach, and Miller (2006). * and ** denote statistical significance at the 10% and 5% level, respectively.

	Whole Syndicate			Lead VC		
	(1)	(2)	(3)	(4)	(5)	(6)
After	0.185**	0.0956	0.00572	0.195**	0.101	0.122
	[0.0714]	[0.0722]	[0.162]	[0.0812]	[0.0736]	[0.186]
Internet VC	0.272**	0.202**	0.191**	0.205*	0.177*	0.160*
	[0.0754]	[0.0763]	[0.0776]	[0.114]	[0.0939]	[0.0936]
After × Internet VC	−0.410**	−0.280**	−0.245**	−0.447**	−0.330**	−0.295**
	[0.0993]	[0.101]	[0.105]	[0.114]	[0.108]	[0.112]
Region FE	No	Yes	Yes	No	Yes	Yes
Sector FE	No	Yes	Yes	No	Yes	Yes
Stage FE	No	Yes	Yes	No	Yes	Yes
After × Region FE	No	No	Yes	No	No	Yes
After × Sector FE	No	No	Yes	No	No	Yes
After × Stage FE	No	No	Yes	No	No	Yes
$\exp(\beta_3)-1$	−0.336	−0.245	−0.217	−0.361	−0.281	−0.255
Spells	3,465	3,451	3,451	3,372	3,353	3,353

Table 5

Non-IT Companies Backed by Internet VCs were Affected: Continuous Internet Exposure, Whole Sample

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

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

Analysis time τ is defined as the time since company i raised its jth round. The variable $After_t$ is an indicator equaling one if the date is after the peak of the technology bubble (March 31, 2000) and zero otherwise. Note $After_t$ is a time-varying covariate i.e. it can change in the middle of a spell. The degree of a venture capital firm k's exposure to internet investments, $InternetExposure_k$, is measured as the percent of the total amount invested by the firm that was invested in companies operating in the internet sector during the ten years leading up to the peak. 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, which is defined to be the one that has invested in the company the longest (ties are broken by cumulative disbursements to the company inclusive of the current round). The sample is restricted to financing rounds of ventured-backed U.S. companies operating in non-IT sectors. The sample period is from March 31, 1997 to March 31, 2003. 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 U.S. companies operating in non-IT sectors. The sample period is from March 31, 1997 to March 31, 2003. Raw coefficients are reported. Standard errors are in brackets and are clustered by portfolio company in the first three columns as well as lead venture firm in the final three columns, following Cameron, Gelbach, and Miller (2006). * and ** denote statistical significance at the 10% and 5% level, respectively.

	Whole Syndicate			Lead VC		
	(1)	(2)	(3)	(4)	(5)	(6)
After	0.132**	0.0835	0.124	0.155**	0.103*	0.240*
	[0.0564]	[0.0588]	[0.116]	[0.0604]	[0.0597]	[0.131]
Internet Exposure	0.673**	0.593**	0.576**	0.457*	0.381	0.404*
	[0.175]	[0.185]	[0.184]	[0.249]	[0.242]	[0.241]
After × Internet Exposure	−1.117**	−0.883**	−0.817**	−0.955**	−0.732**	−0.765**
	[0.230]	[0.243]	[0.243]	[0.261]	[0.267]	[0.269]
Region FE	No	Yes	Yes	No	Yes	Yes
Sector FE	No	Yes	Yes	No	Yes	Yes
Stage FE	No	Yes	Yes	No	Yes	Yes
After × Region FE	No	No	Yes	No	No	Yes
After × Sector FE	No	No	Yes	No	No	Yes
After × Stage FE	No	No	Yes	No	No	Yes
Spells	6,889	6,867	6,867	6,623	6,585	6,585

Table 6

Non-IT Companies Backed by Internet VCs were Affected: Continuous Internet Exposure, Quarterly Internet VC Flows, Whole Sample

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

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

Analysis time τ is defined as the time since company i raised its jth round. The variable $\log(InternetFlows_t)$ represents the log of quarterly aggregate flows into (U.S. based, independent, private) internet-specific venture funds, from *ThompsonOne*. Flows are converted to 2000 dollars using the GDP deflator. The variable $After_t$ is an indicator equaling one if the date is after the peak of the technology bubble (March 31, 2000) and zero otherwise. Note $\log(InternetFlows_t)$ and $After_t$ are time-varying covariate i.e. they can change in the middle of a spell. The degree of a venture capital firm k's exposure in internet investments, $InternetExposure_k$, is measured as the percent of the total amount invested by the firm that was invested in companies operating in the internet sector during the ten years leading up to the peak. 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, which is defined to be the one that has invested in the company the longest (ties are broken by cumulative disbursements to the company inclusive of the current round). 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 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 and quarter in the first three columns as well as lead venture firm in the final three columns, following Cameron, Gelbach, and Miller (2006). * and ** denote statistical significance at the 10% and 5% level, respectively.

	Whole Syndicate			Lead VC		
	(1)	(2)	(3)	(4)	(5)	(6)
log(Internet Flows)	0.0139	0.0123	0.00134	0.00837	0.00933	−0.00548
	[0.0169]	[0.0181]	[0.0266]	[0.0220]	[0.0226]	[0.0239]
Internet Exposure	0.107	0.163	0.150	0.0110	0.0571	0.0619
	[0.160]	[0.146]	[0.144]	[0.200]	[0.173]	[0.173]
log(Internet Flows) × Internet Exposure	0.161**	0.169**	0.146**	0.171**	0.170**	0.166**
	[0.0594]	[0.0540]	[0.0483]	[0.0730]	[0.0713]	[0.0639]
Region FE	No	Yes	Yes	No	Yes	Yes
Sector FE	No	Yes	Yes	No	Yes	Yes
Stage FE	No	Yes	Yes	No	Yes	Yes
log(Internet Flows) × Region FE	No	No	Yes	No	No	Yes
log(Internet Flows) × Sector FE	No	No	Yes	No	No	Yes
log(Internet Flows) × Stage FE	No	No	Yes	No	No	Yes
Spells	6,889	6,867	6,867	6,623	6,585	6,585

Table 7

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

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

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

Analysis time τ is defined as the time since company i raised its jth round. The variable $\log(InternetFlows_t)$ represents the log of quarterly aggregate flows into (U.S. based, independent, private) internet-specific venture funds, from *ThompsonOne*. Flows are converted to 2000 dollars using the GDP deflator. The variable $After_t$ is an indicator equaling one if the date is after the peak of the technology bubble (March 31, 2000) and zero otherwise. Note $\log(InternetFlows_t)$ and $After_t$ are time-varying covariate i.e. they can change in the middle of a spell. The degree of a venture capital firm k's exposure in internet investments, $InternetExposure_k$, is measured as the percent of the total amount invested by the firm that was invested in companies operating in the internet sector during the ten years leading up to the peak. 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, which is defined to be the one that has invested in the company the longest (ties are broken by cumulative disbursements to the company inclusive of the current round). 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 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 and quarter in the first three columns as well as lead venture firm in the final three columns, following Cameron, Gelbach, and Miller (2006). * and ** denote statistical significance at the 10% and 5% level, respectively.

	Whole Syndicate			Lead VC		
	(1)	(2)	(3)	(4)	(5)	(6)
log(Internet Flows)	0.0168	0.0153	0.00274	0.0115	0.0126	−0.00396
	[0.0164]	[0.0173]	[0.0265]	[0.0217]	[0.0223]	[0.0242]
Internet Exposure	0.129	0.185	0.171	0.0336	0.0799	0.0852
	[0.164]	[0.152]	[0.150]	[0.200]	[0.175]	[0.175]
log(Internet Flows) × Internet Exposure	−0.0167	−0.0197	−0.0350	−0.0427	−0.0517	−0.0532
	[0.0939]	[0.0882]	[0.0828]	[0.0994]	[0.0990]	[0.0942]
log(Internet Flows) × Internet Exposure × After	0.234**	0.252**	0.242**	0.288**	0.301**	0.296**
	[0.101]	[0.0976]	[0.0937]	[0.0956]	[0.0927]	[0.0905]
Region FE	No	Yes	Yes	No	Yes	Yes
Sector FE	No	Yes	Yes	No	Yes	Yes
Stage FE	No	Yes	Yes	No	Yes	Yes
log(Internet Flows) × Region FE	No	No	Yes	No	No	Yes
log(Internet Flows) × Sector FE	No	No	Yes	No	No	Yes
log(Internet Flows) × Stage FE	No	No	Yes	No	No	Yes
Spells	6,889	6,867	6,867	6,623	6,585	6,585

Table 8
Internet VCs Became More Likely to Drop Out of Rounds After Collapse

This table shows the results of estimating probit models of the form,

$$\Pr(VCDropout_{ijkt}) = \Phi(\beta_0 + \beta_1 After_t + \beta_2 InternetExposure_k + \beta_3 After_t \times InternetExposure_k + \boldsymbol{\delta}'\boldsymbol{x}_{ijt}).$$

Observations are at the company-round-VC level. For each continuation round raised by a company, there is an observation for each venture firm that participated in the previous round. If the venture firm participated in the current round $VCDropout_{ijkt}$ equals zero; otherwise, if the venture firm did not participate $VCDropout_{ijkt}$ is equal to one. One exception to this rule is made if the venture firm is observed participating again in subsequent rounds of the company. Then the firm is considered a participant in the current round as its omission is taken to be a data error. The variable $After_t$ is an indicator equaling one if the date of the round is after the peak of the technology bubble (March 31, 2000) and zero otherwise. The degree of a venture capital firm k's exposure in internet investments, $InternetExposure_k$, is measured as the percent of the total amount invested by the firm that was invested in companies operating in the internet sector during the ten years leading up to the peak. 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 U.S. companies operating in non-IT sectors. The sample period is from March 31, 1997 to March 31, 2003. Raw coefficients are report with marginal effects alongside. Standard errors are in brackets and are clustered by company and venture firm in all specifications, following Cameron, Gelbach, and Miller (2006). * and ** denote statistical significance at the 10% and 5% level, respectively.

	(1) Coef	Marginal	(2) Coef	Marginal	(3) Coef	Marginal
Internet Exposure	−0.155	−0.0286	−0.114	−0.0253	−0.116	−0.0268
	[0.160]		[0.158]		[0.159]	
After	−0.0196	−0.00372	−0.0919	−0.0199	−0.139	−0.0305
	[0.0675]		[0.0688]		[0.128]	
After × Internet Exposure	0.485**	0.0957**	0.570**	0.129**	0.529**	0.119**
	[0.215]		[0.219]		[0.221]	
Region FE	No		Yes		Yes	
Sector FE	No		Yes		Yes	
Stage FE	No		Yes		Yes	
After × Region FE	No		No		Yes	
After × Sector FE	No		No		Yes	
After × Stage FE	No		No		Yes	
Observations	11,823		11,782		11,782	

Table 9

Internet VCs Had Increased Fundraising Difficulty After Collapse

Each column of this table reports the results of re-estimating the Cox proportional hazard models of Tables 4 through 6 at the venture firm level. Specifically, rather than estimating the hazard of a portfolio company raising a continuation round from venture firms, the hazard of a venture firm raising a follow-on fund from limited partners is now estimated. Analysis time τ is defined as the time since venture firm k raised its last fund. The indicator variable $InternetVC_{ij}$ is set equal to one if the venture firm is in the top quartile of $InternetExposure_{ij}$ and zero if it is in the bottom quartile. The variable $After_t$ is an indicator equaling one if the date is after the peak of the technology bubble (March 31, 2000) and zero otherwise. The variable $\log(InternetFlows_t)$ represents the log of quarterly aggregate flows into (U.S. based, independent, private) internet-specific venture funds, from *ThompsonOne*. Flows are converted to 2000 dollars using the GDP deflator. Note $After_t$ and $log(InternetFlows_t)$ are time-varying covariate i.e. they can change in the middle of a spell. The degree of a venture capital firm k's exposure in internet investments, $InternetExposure_k$, is measured as the percent of the total amount invested by the firm that was invested in companies operating in the internet sector during the ten years leading up to the peak. 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, following Cameron, Gelbach, and Miller (2006). * and ** denote statistical significance at the 10% and 5% level, respectively.

	(1)	(2)	(3)
After	0.0443	-0.179^{*}	
	[0.140]	[0.0953]	
Internet VC	0.414^{**}		
	[0.180]		
After × Internet VC	-0.649^{**}		
	[0.185]		
Internet Exposure		0.512^{**}	-0.00465
		[0.205]	[0.221]
After × Internet Exposure		-0.873^{**}	
		[0.259]	
log(Internet Flows)			0.203^{**}
			[0.0707]
log(Internet Flows) × Internet Exposure			0.317^{**}
			[0.103]
Spells	729	1,446	1,446

Table 10

Companies Backed by VCs Late in Fundraising Cycle were Most Affected

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

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

Analysis time τ is defined as the time since company i raised its jth round. The variable $After_t$ is an indicator equaling one if the date is after the peak of the technology bubble (March 31, 2000) and zero otherwise. Note $After_t$ is a time-varying covariate i.e. it can change in the middle of a spell. The degree of a venture capital firm k's exposure to internet investments, $InternetExposure_k$, is measured as the percent of the total amount invested by the firm that was invested in companies operating in the internet sector during the ten years leading up to the peak. 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, which is defined to be the one that has invested in the company the longest (ties are broken by cumulative disbursements to the company inclusive of the current round). 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 $InternetExposure_k$. 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 U.S. companies operating in non-IT sectors. The sample period is from March 31, 1997 to March 31, 2003. Raw coefficients are reported. Standard errors are in brackets and are clustered by portfolio company in the first three columns as well as lead venture firm in the final three columns, following Cameron, Gelbach, and Miller (2006). * and ** denote statistical significance at the 10% and 5% level, respectively.

	Whole Syndicate			Lead VC		
	(1)	(2)	(3)	(4)	(5)	(6)
After	0.0287	−0.0522	−0.149	0.0521	−0.0112	0.0727
	[0.0920]	[0.0936]	[0.150]	[0.0947]	[0.0926]	[0.147]
Internet Exposure	0.180	0.215	−0.313	0.0258	0.114	−0.0919
	[0.269]	[0.277]	[0.384]	[0.357]	[0.350]	[0.429]
Years Since Raised	−0.0611**	−0.0463**	−0.0518**	−0.0443*	−0.0278	−0.0274
	[0.0193]	[0.0196]	[0.0200]	[0.0234]	[0.0216]	[0.0222]
After × Internet Exposure	−0.546	−0.204	0.351	−0.218	0.106	0.212
	[0.390]	[0.396]	[0.511]	[0.398]	[0.399]	[0.495]
After × Years Since Raised	0.0329	0.0469	0.0580	0.0425	0.0543*	0.0588*
	[0.0343]	[0.0345]	[0.0356]	[0.0322]	[0.0312]	[0.0321]
Internet Exposure × Years Since Raised	0.113	0.0788	0.0984	0.120	0.103	0.0840
	[0.0858]	[0.0879]	[0.0877]	[0.104]	[0.0990]	[0.1000]
After × Internet Exposure ×	−0.338**	−0.393**	−0.396**	−0.528**	−0.613**	−0.586**
Years Since Raised	[0.167]	[0.169]	[0.170]	[0.178]	[0.176]	[0.180]
Region FE	No	Yes	Yes	No	Yes	Yes
Stage FE	No	Yes	Yes	No	Yes	Yes
Sector FE	No	Yes	Yes	No	Yes	Yes
After × Region FE	No	No	Yes	No	No	Yes
After × Sector FE	No	No	Yes	No	No	Yes
After × Stage FE	No	No	Yes	No	No	Yes
Internet Exposure × Stage FE	No	No	Yes	No	No	Yes
After × Internet Exposure × Stage FE	No	No	Yes	No	No	Yes
Spells	5,985	5,969	5,969	5,558	5,531	5,531

Table 11

Companies Backed by VCs Late in Fundraising Cycle were Most Affected: Young Versus Old VCs

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

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

Analysis time τ is defined as the time since company i raised its jth round. The variable $After_t$ is an indicator equaling one if the date is after the peak of the technology bubble (March 31, 2000) and zero otherwise. Note $After_t$ is a time-varying covariate i.e. it can change in the middle of a spell. The degree of a venture capital firm k's exposure to internet investments, $InternetExposure_k$, is measured as the percent of the total amount invested by the firm that was invested in companies operating in the internet sector during the ten years leading up to the peak. Internet exposure for the syndicate backing the jth round of company i is then calculated as the $InternetExposure_k$ of the lead venture firm in the round, which is defined to be the one that has invested in the company the longest (ties are broken by cumulative disbursements to the company inclusive of the current round). 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 $InternetExposure_k$. When company controls are included, the most prevalent categories (Northern California, expansion, and medical/health) are omitted. The first three columns show results for rounds backed by lead venture firms less than six years old at the peak. The final three columns show results for rounds backed by lead venture firms greater than six years old at the peak. Region/stage/sector controls are estimated based on the whole sample in all specifications. The sample is restricted to financing rounds of ventured-backed U.S. companies operating in non-IT sectors. The sample period is from March 31, 1997 to March 31, 2003. Raw (unexponentiated) Coefficients are reported. Standard errors are in brackets and are clustered by portfolio company as well as lead venture firm, following Cameron, Gelbach, and Miller (2006). * and ** denote statistical significance at the 10% and 5% level, respectively.

	Lead VC Age $<$ 6 Years			Lead VC Age $\geq$ 6 Years		
	(1)	(2)	(3)	(4)	(5)	(6)
After	−0.213	−0.142	−0.0909	0.136	0.0407	0.104
	[0.202]	[0.192]	[0.233]	[0.123]	[0.115]	[0.165]
Internet Exposure	−0.529	−0.0594	−0.400	−0.153	−0.195	−0.332
	[0.567]	[0.566]	[0.625]	[0.483]	[0.434]	[0.516]
Years Since Raised	−0.102	−0.0327	−0.0482	−0.0426*	−0.0308	−0.0284
	[0.104]	[0.108]	[0.109]	[0.0251]	[0.0229]	[0.0236]
After × Internet Exposure	0.866	0.832	1.050	−0.662	−0.220	−0.0920
	[0.607]	[0.607]	[0.710]	[0.594]	[0.568]	[0.627]
After × Years Since Raised	0.140	0.0904	0.110	0.0129	0.0315	0.0355
	[0.109]	[0.112]	[0.112]	[0.0382]	[0.0375]	[0.0383]
Internet Exposure × Years Since Raised	0.636*	0.466	0.554	0.0898	0.0937	0.0614
	[0.342]	[0.359]	[0.370]	[0.114]	[0.107]	[0.110]
After × Internet Exposure ×	−1.312**	−1.245**	−1.328**	−0.288	−0.386*	−0.356*
Years Since Raised	[0.407]	[0.418]	[0.436]	[0.209]	[0.212]	[0.214]
Region FE	No	Yes	Yes	No	Yes	Yes
Stage FE	No	Yes	Yes	No	Yes	Yes
Sector FE	No	Yes	Yes	No	Yes	Yes
After × Region FE	No	No	Yes	No	No	Yes
After × Sector FE	No	No	Yes	No	No	Yes
After × Stage FE	No	No	Yes	No	No	Yes
Internet Exposure × Stage FE	No	No	Yes	No	No	Yes
After × Internet Exposure × Stage FE	No	No	Yes	No	No	Yes
Spells	1,254	1,250	1,250	4,304	4,281	4,281

Table 12

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

This table shows the results of estimating equations of the form,

$$\lambda_i = \exp(\beta_0 + \beta_1 InternetExposure_i + \boldsymbol{\delta}'\boldsymbol{x}_i),$$

where λ is the intensity parameter of the negative binomial distribution. In columns one and three i indexes venture backed portfolio companies and λ_i represents patenting intensity before March 31, 2000. Companies differ in terms of their exposure time due to the fact that they received their first financing round at different dates. This is adjusted for by altering the log likelihood function appropriately (Cameron and Trivedi, 1998). In columns two and four, i indexes individual patents and λi represents citation intensity. All patents have the same exposure time in this case as only citations that occurred in the three years following the date a patent was granted are counted. Also in columns two and four $\ln(\gamma_i)$ is included as a dependent variable with its coefficient constrained to equal one, following Lerner, Sorensen, and Strömberg (2008). The variable γ_i represents the mean number of citations received (in the first three years) for all patents with the same USPTO patent class and grant year as patent i. This procedure takes into account the fact that patents with different classes and grant years differ in terms of their baseline citation intensity. The variable $InternetExposure_i$ represents the internet exposure of the syndicate backing the first round of company i. The degree of a venture capital firm k's exposure to internet investments, $InternetExposure_k$, is measured as the percent of the total amount invested by the firm that was invested in companies operating in the internet sector during the ten years leading up to the peak. Internet exposure for the syndicate backing the first 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, which is defined to be the one that has invested in the company the longest (ties are broken by cumulative disbursements to the company inclusive of the current round). 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 date 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 two as well as by lead venture firm in column four following Cameron, Gelbach, and Miller (2006). * and ** denote statistical significance at the 10% and 5% level, respectively.

	Whole Syndicate		Lead VC	
	(1) Total Patents	(2) Relative Citations	(3) Total Patents	(4) Relative Citations
Internet Exposure	2.990	2.884	1.000	0.932
	[2.253]	[3.439]	[2.562]	[3.072]
Region FE	Yes	No	Yes	No
Sector FE	Yes	No	Yes	No
Exposure Time Adj	Yes	No	Yes	No
Classification-Year Adj	No	Yes	No	Yes
Observations	477	1,683	462	1,579