Venture Capital and Innovation

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ABSTRACT

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This dissertation delves into the relation between venture capital and innovation. The existing literature usually addresses this question by using industry-level data. In contrast, the analysis here relies on data at the company level on patents invented in venture-backed companies. The dissertation has four parts. The first part, a paper coauthored with my advisors Bruce Kogut and Morten Sorensen, examines the relation between venture capital and the rate and quality of companies' innovative activity. We compare the number of patent filings, and the quality of innovations, before and after companies are first financed by a venture capital investor. As an attempt to control for the endogeneity of venture capital investments we exploit amendment by the Texas Legislature that freed public state pension funds in Texas to invest in venture capital. Our results suggest that venture funding increases the rate of companies' innovative activity. Interestingly, we also find that venture capital is associated with a decrease in the quality of companies' research output. The second part estimates the effect of venture capital on the diffusion of knowledge. I compare citations to patents invented in venture-backed companies to those of comparable patents invented elsewhere. To isolate the causal effect, I exploit time variation in the assets of state pension funds that allocate capital to venture capital. This variation provides a valid instrument if the effect of changes in innovation opportunities within a state is uniform across local patents in the same technology-class and vintage-year. I find that after

venture funding annual citations to a given patent increase 19% relative to the citations of comparable patents. Additional results are consistent with two mechanisms: venture capital investors certify the value of patents to the general public and facilitate communication among companies in their portfolios. The third part of this dissertation explores whether the strategic interaction of companies in the same venture capital network affects the direction of companies' innovative activity. Theoretically, this effect is not clear. Whereas the presence of common investors can stir companies' research in the same direction by facilitating knowledge spillovers, competition for the same financial resources may undermine the incentives of companies in the same venture capital network to collaborate, or even work in similar areas. To test this question empirically I use the propensity of patent citations among pairs of companies as a measure of the similarity in companies’ research. To reduce concerns of strategic investment by venture capital investors, I control in the estimation for the technological similarity and geographical co-location of companies. Consistent with venture capitalists facilitating the diffusion of knowledge across the companies they finance I find that companies in the same venture capital network produce similar innovations. Interestingly, I also find that this convergence in innovation is only true for companies that are not competing for the same financial resources, specifically, those pairs of companies that are geographically distant or work in different technological areas and industries. Results suggest that the optimal strategy for companies that are competing for the same financial resources is to differentiate and pursue different lines of research. Finally, the fourth part od this dissertation describes in detail the construction of the dataset.

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1 Venture Capital and Innovative Activity (with Bruce Kogut and Morten Sorensen)

The impact of Venture Capital (VC) on innovation has been a popular topic in the financ literature for the past two decades. Although most of the empirical work at the industry level find that VC increases innovative activity (e.g., Kortum and Lerner (2000), Mollica and Zingales (2007), Hirukawa and Ueda (2008) and Popov and Roosenboom (2009)), evidence at the company level suggests that this impact is weak at best (e.g., Engel and Keilbach (2007), Caselli et al. (2009), and Stuck and Weingarten (2005)).

Theoretically, even if VC spurs innovation at the industry level it is not clear that VCs necessarily encourage the innovative activity of the companies they invest in. Whereas VC can positively affect overall industrial Research and Development (R&D) by facilitating the diffusion of technical knowledge,[1] or increasing access to potential risk capital, once companies are VC finance incentives to innovate may be curtailed. For example, the competition for future financia resources inside VC portfolios can push companies to exert more effort on the development part of R&D relative to research. In light of these complex trade-offs, the studies that use data at the company and at the industry level do not necessarily offer contradictory evidence. More systematic evidence is required to have a better understanding on how VC interacts with innovation.

This chapter provides new evidence on the effect of VC on innovative activity using data at the company level, and departs from the existing literature on two accounts. First, we rely on data for US-based startups. In contrast, existing research at the company level uses data for European-based startups. This is an important departure as the landscape for financin innovation has been shown to be fundamentally different across these two regions. While the role of VC in the U.S. is

[1] For more on this topic see Chapter 2.

mainly to target high-risk, high-payoff innovations, in Europe this role seems to be partially fille by business-groups (Belenzon et al. (2010)).[2] Thus, it is likely that the types of companies that are VC finance in each region are different, and that the effect of VC on companies' innovation may differ. In addition, the existing evidence is for the most part restricted to startups that ultimately went public (e.g., Stuck and Weingarten (2005) and Caselli et al. (2009)). Since approximately only a third of the companies that are VC-backed go public, and going public has its own effect on innovation (e.g., Bernstein (2012)), our work offers a more comprehensive analysis.

The second departure from the existing literature is that we explore how VC affects not only the rate of innovative activity but also its composition. Following a growing literature that uses patent-based metrics to characterize innovation at the company level (e.g., Seru (2012) Lerner et al. (2011), Bernstein (2012)), we use data on patent citations to explore how VC affects the quality, novelty, and nature of the research output of companies.

There are two main findings Our results suggest that venture funding increases the rate of companies' innovative activity as measured by patent filings This result is consistent with the evidence at the industry level, and stands to contrast with existing evidence at the company level. Interestingly, we fin that the type of innovations produced by companies also changes after venture funding. Mainly, VC is associated with a decrease in the quality of companies' research output.

One interpretation of the finding is that they simply reflec endogenous VC choices. For example, VCs may invest in companies when they expect a surge of patent filing following an innovative breakthrough. As an attempt to control for endogeneity, we exploit an amendment by the Texas Legislature that freed public state pension funds in Texas to invest in VC. Unlike private retirement systems that are governed by the federal Employee Retirement Security Act (ERISA),

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[2]The fundamental reasons for this difference are that in Europe the capitalization of R&D is on average lower than in the U.S., and the stigma of failure is also higher (Belenzon et al., 2010).

the investment policy of public pension funds is governed by state laws. In contrast to private pension funds, most public pension funds were not explicitly allowed to invest in high-risk assets until much later than the ERISA clarificatio in 1979. In fact, by 1990 almost 30% of public retirement funds were prohibited from investments in VC.[3] The clarificatio by the Texas Legislature led to an increase in the funds committed to VC by local public pension funds, and is useful to identify the causal impact of venture funding on innovative activity because it is likely unrelated to the arrival of innovation opportunities. Using an instrumental variable approach based on this intuition, we fin that the increase in the rate of innovative activity following venture funding, as well as the decrease in the quality of innovations, are not be exclusively explained by VC selection.

This paper chapter to the literature that examines the relation between innovation and different dimensions of corporate financ such as: institutional ownership (Aghion et al. (2009)), the decision to go public (Bernstein (2012)), the decision to merge (Seru (2012)), financia constraints (Almeida et al. (2013)), corporate governance (Chemmanur and Tian (2012)), and organizational form (e.g., Belenzon et al. (2010) and Belenzon et al. (2012)). Our work is closest to Lerner et al. (2010) which uses a similar framework to study the effect of Leveraged Buyouts (LBOs) on innovation. Taken together, our finding suggest that LBOs and VC, the two most dominant forms of Private Equity (PE) in the US, interact with innovation very differently. While LBOs are associated with an increase in the quality of their targets' innovations, innovation novelty decreases after venture funding. In addition, LBOs seem to have no effect on the scale of innovative activity, while VC is associated with an increase in companies' patent filings The difference in the interaction between LBO and VC with innovation is consistent with the differences across these PE funds' investment strategies. While LBOs target companies that have potential for improvement, VCs target companies that are very close to their innovative peak, and ripe for monetization.

[3] Author's calculations based on work by Snell and Wolfe (1990). The authors used a survey among 77 state retirement systems and inquired about investment restrictions. About half of those funds reported having statutory restrictions on their investments.

This chapter also relates to the literature that examines the impact of financia development on the real economy (e.g., LaPorta et al. (1999) and Rajan and Zingales (1998)). Given existing evidence of a weak effect of venture funding on the innovative activity for European-based startups, our contrasting finding for US-based startups are broadly consistent with Belenzon et al. (2010), who fin a different role for VC in the U.S. and in Europe.

The rest of this chapter is organized as follows. In Section 1.1 we describe the data and the empirical methodology. Section 1.1 summarizes the results. Conclusions and directions for future research are presented in Section 1.3.

1.1 Data and Empirical Analysis

1.1.1 Sample Composition

The data in this analysis combines information on VC investments in US-based startups with patent filing of U.S. companies. A thorough description of the construction of the sample can be found in the Appendix. For this chapter, we subset the data to companies with at least one U.S. utility patent application in the period from the calendar year starting 3 years before, to the calendar year starting 5 years after, the year of the (first VC investment. This yields a sample of 36,980 patents file by 4,169 VC-backed companies. For large parts of the analysis we calculate the number of citations a patent receives over the three years following the grant date. For these parts, we exclude patents granted after December 2004, which restricts the sample to 21,138 patents file by 3,231 VC-backed companies.

Table 1.1 shows the composition of the fina sample in terms of patents and companies. Panel A in Table 1.1 breaks down the sample by year in which the companies were firs finance by a VC. The distribution of VC investments is concentrated in the second half of the 1990s and the firs half of the 2000s. This concentration reflect both the increasing volume of VC investments during these years, and the growing representation of technology companies, which have more patents. Panel A also breaks down the sample by type of VC exit. The type of exit is recorded by SDC Thompson at the end of 2009. A third of the sample corresponds to investments that were still active by the end of the sample. The most popular type of exit are Acquisitions. This category is followed by: Initial Public Offering (IPO), company death (Defunct), and Other.

Panel A in Table 1.1 also displays the timing of the patent applications and awards. The application dates extend from 1976 (3 years before the firs VC investment) to 2008.

Panel B in Table 1.1 breaks the sample down by industry classes. The distribution of companies is concentrated in Communications and Media, however, the distribution of patents is more evenly spread out across industries. This difference in distributions reflect the different patent propensities across industries.

1.1.2 Characterizing innovative activity

We focus on the size, quality and nature of companies' patent portfolios to characterize innovative activity. This section briefl describes the different patent-based metrics and present summary statistics.

Patent filing and the rate of innovative activity We capture the rate of companies' innovative activity by tracking companies' yearly patent filings Patent filing are timed using applications dates as these approximate the timing of invention more accurately than grant dates. Table 1.2 compares patent activity around the VC investment. Companies fil 0.37 patents a year on average before venture funding. After VC investment mean annual patent filing increase to 1.09. The difference is statistically significant

Citation counts and the quality of innovative activity Following the innovation literature, we use the citation count as a measure of the quality, or economic importance of the patent (e.g., Hall et al. (2001) and Hall et al. (2005)). The citation count corresponds to the number of times the patent has been cited by other patents in the calendar years of the patent grant and the 3 subsequent years. Panel B in Table 1.2 compares the citation count for patents file before and after companies are firs finance by a VC. On average, patents file before the VC investment are cited 9.192 times in the firs three years after they are granted. In contrast, patents file after the VC investment are cited 9.158 times over the 3 years after the grant date. This decrease in the citation count is not statistically significant

We distinguish between self-citations and non-self-citations, which correspond to citations made, and not made, by the filin company, respectively. Self-citations are traditionally regarded as a measure of the degree in which companies are able to internalize the profit of their innovations. As a consequence, the non-self-citation count is considered to be a better measure of patent quality. Panel B in Table 1.2 reports average self-citation and non-self-citation counts for patents file in the years around the VC investments (self-cites and non-self-cites, respectively). Self-citations increase after VC investment and the increase is significan at the 10% level. In contrast, non-self-citations decrease, although the difference is not statistically significant

Following Lerner et al. (2010), we control for trends in citation rates at the grant-year and technology-class level using a set of matching patents define as follows. For every patent in the sample we determine all U.S. patents assigned to the same United States Patents and Trademark Offic (USPTO) technology-class and with the same grant-year.[4]

[4]At present, the USPTO has assigned more than 400 technology-classes, examples of which include Radio Wave Antennas and Wheel Substitutes for Land Vehicles.

Using the matching patents, we construct a citation baseline as:

$$b = \frac{Total\ Cites}{Number\ of\ Matching\ Patents}, \tag{1}$$

where *Total Cites* corresponds to citations received by matching patents in the calendar years of the patent grant and the 3 subsequent years. We repeat this procedure for each type of citation count and construct analogous baselines.

Panel B in Table 1.2 reports scaled measures of patent quality, calculated as the ratio between each type of citation count and the corresponding citation baseline. Scaled citation counts before the VC investment are statistically different from one, suggesting that the VC firm are targeting companies with unusual patenting activity. Post-VC investment there is a slight decrease in the scaled non-self-citation count and an increase in the scaled self-citation count. However, none of these changes in scaled citation counts are statistically significant

Distribution of citations across technology-classes and the nature of innovations Following Hall et al. (2001) we study the nature of patents by looking at the patents' originality and generality measures. These measures are based on the distribution across technology-classes of the patents cited, or of the patents that cite, the innovations in the sample. In detail, the originality measure is calculated as one minus the Herf ndahl index of the cited patents across technology-classes.[5] The intuition is that patents that combine existing knowledge from few technology-classes to create something new (and useful) probably constitute more marginal improvements relative to patents that combine more different ideas ex-ante. The generality measure is calculated analogously to the originality measure, but using the distribution across technology-classes of the citing patents.

Panels C and D in Table 1.2 compare the originality and generality of patents file before and

[5] We report results using adjusted measures of originality and generality based on the bias-correction described in Jaffe and Trajtenberg (2002).

after the VC investment. We also include a measure of scaled originality (generality), calculated as the ratio between the originality (generality) of the patents in the sample, and the average originality (generality) of matching patents. Although there is evidence of a slight decrease in both the originality and generality of patents file after venture funding, these changes are not statistically significant

1.1.3 Econometric Modeling Strategy

Modeling the rate of innovative activity Consider the firs moment of the relationship between the rate of innovative activity, as measured by $Patents_{it}$, the number of ultimately successful patent applications of company i in period t, and VC investments, as measured by $After\ VC_{it}$, a dummy denoting observations after the VC investment. The conditional expectation of this measure of innovation activity is:

$$E(Patents_{it}|\eta_i, \tau_t) = \exp(\alpha After VC_{it} + \eta_i + \tau_t). \tag{2}$$

We adopt a log-link formulation, because of the count nature of the data. As is well known, given the same firs moment, alternative estimators can be generated depending on the different assumptions concerning the error term. Our main analysis uses a Poisson model where the mean equals the variance. However, since we allow the standard errors to have arbitrary heteroscedasticty and autocorrelation (i.e., by clustering standard errors at the company level) the exact functional form of the error distribution is not so important (Aghion et al. (2009)).

The model includes fi ed-effects for each year to control for the time variation in the propensity to patent. We introduce company fi ed-effects, η_i, using the conditional fi ed-effects Poisson model of Hausman et al. (1984). To address the truncation of the data we subset the sample to VC investments made until 1999 and report results for this subsample in the tables. While we observe some successful patent fi ings in the fina years of the sample, many applications that were file during these years were likely still not issued as of December 2008.[6] Because the later years in the sample, where this truncation will be worse, are disproportionately likely to be in the years after a VC investment, this effect may bias the counts of patent filings In the sub-sample of VC investments prior to 1999 effects due to not-yet-issued patent applications should be reduced.

We compare the results of this count data model to OLS estimates, i.e.,

$$\ln(Patents_{it} + 1) = \alpha AfterVC_{it} + \eta_i + \tau_t + \varepsilon_{it}, \tag{3}$$

where we use as dependent variable an arbitrary re-scaling in order to avoid dropping all observations of companies with zero patent filings

Modeling the quality and nature of innovative activity Consider now the firs moment of the relationship between the quality of innovative activity, as measured by $Cites_{it}^{k}$, the number of citations received by patent k file by company i, in period t, (or any other measure of quality or nature of innovations describe in Section 1.2) and VC investments, as measured by $After\ VC_{it}$, the dummy denoting observations after the VC investment. The conditional expectation of this measure of quality of innovative activity is:

$$E(Cites_{it}^{k}|\eta_i, \tau_t) = \exp(\beta AfterVC_{it} + \eta_i + \ln(b)), \tag{4}$$

where b corresponds to the citation baseline explained above. We use the citation baseline as an offset in the estimation of this model in order to control for changes in citation behavior and the industry composition of companies over time. By offsetting the citation baseline, we force the expected value of citations received by patent k to equal the average number of citations received

[6] The average lag between grant and application years in the sample is of 2.3 years.

by similar patents in the same technology-class and granted the same year. Note that b absorbs all time variation in patent citations at the technology-class and grant-year level, hence, we do not include time fi ed-effects in the estimation. The estimated coefficien for β reflect the relative citation intensities of patents granted to companies in our sample compared to the matching patents.

The model introduces company fi ed-effects, η_i, to control for the heterogeneity in the quality and performance of companies that characterizes the VC industry. The methodology follows closely Lerner et al. (2011), and is similar to the within-company estimators of Seru (2007) and Bernstein (2012).

Similarly to the analysis of the rate of innovative activity, we compare the results of the count data models to OLS estimates, i.e.,

$$\ln(Scaled\_Cites_{it}^{k} + 1) = \beta AfterVC_{it} + \eta_i + \varepsilon_{it}, \tag{5}$$

where $Scaled\_Cites_{it}^{k}$ corresponds to scale citations.[7] The well known disadvantage of these models is the arbitrary re-scaling needed to avoid dropping all observations of patents with zero-citations.

Selection Issues The coefficien on $AfterVC_{it}$ in the regression models (2)-(5) may be biased for many reasons. The main concern is that VCs select companies to invest in on the basis of characteristics that are observable to them but not to us. For example, VCs might invest in companies when they anticipate a surge in innovation. As an attempt to tackle this issue we exploit an amendment in the Texas legislature in 1999 that freed public pension funds in Texas to invest in VC. This clarificatio was prompted by the Board of the Texas Teacher Retirement System (TRS),

[7] Recall from Section 1.2.2 that scaled citations are define as the ratio between citations and the citiation baseline: $Scaled\_Cites_{it}^{k} = Cites_{it}^{k}/b$.

that asked the Attorney General to clarify the definitio of securities as used in Section 67, Article XVI, of the Texas Constitution. The Attorney General issued the formal public opinion No. JC-0043, clarifying that the TRS could invest in instruments define as securities under the Uniform Commercial Code (UCC) definition Following the issuance of this Opinion, the Texas Legislature amended the Texas Government Code (Section 825.301) to add a definitio of securities which explicitly includes interests in limited partnerships among others. Consequently, the allocation of local public pension funds to venture capital increased. In particular, the allocation of TRS to VC quintupled from 1998 to 2002 (went from 44 million to 233 million). This change in the Texas Government Code was later reinforced by the adoption of the "prudent investor rule" as the standard for governance of the asset allocation of state and local pension funds in 2004 (Title 9, Section 117.001 of the Uniform Prudent Investor Act).

The amendment in the Texas legislature should identify the effect of VC on innovative activity, because it is unlikely to be related to the arrival of innovation opportunities. The main motivation behind the request for the clarificatio was a desire to eliminate investment uncertainty as advised by external auditors of the TRS.[8] To capture this policy shift empirically one may firs think of subsetting the sample to companies headquartered in Texas, and using a dummy variable taking on the value of zero through 1999 and one thereafter. The problem with this simple approach is that patenting rates in Texas may change over time for a variety of reasons, including changes in the behavior of companies around the rise and bust of the dot-com. Using this strategy we would not to be able to disentangle the shift in venture fund raising from that in the propensity to patent.

The Texas amendment, however, should have had a predictably greater impact on innovative

[8]The Texas State Auditor's Offic contracted Independent Fiduciary Services (IFS) in 1996 to perform an independent evaluation of the TRS investment program and practices on behalf of the Legislative Audit Committee. The IFS report recommended granting TRS authority to invest in a broader range of asset classes than was permitted. Subsequently, the Legislature took action to broaden the range of permitted investments (or at least help alleviate doubts about the scope of permitted investments), such as the clarificatio regarding admissible securities of 1999. Importantly, the main motivation for these changes was to reduce uncertainty regarding authority to invest as it was seen to impede the ability of the Board to optimally manage and diversify its portfolio.

activity in companies headquartered in Texas, as those likely experienced a greater increase in the probability of being selected by a VC than companies elsewhere. Public pension funds have been shown to be locally biased in their PE investments (Hochberg and Rauh (2010)), therefore, VC firm headquartered in Texas should have experienced a greater increase in funding after the amendment. In addition, at the time of the amendment the Texas constitution imposed travel limitations for pension funds' officials which curtailed the ability of pension funds to conduct necessary due diligence of investments outside the state (see for example: IFS (2002)), and likely biased their PE investments to local funds. At the same time, VC firm are also home-biased in their portfolio company investments (e.g., Lerner (1995) and Sorenson and Stuart (2001)). The combination of these two home-biases suggests that after the 1999 amendment companies headquartered in Texas should have experienced a greater increase in the probability of being finance by a VC than those in other states, and thus, a greater bust in patenting.

We implement the instrumental variable approach by restricting the sample to companies headquartered in Texas and its neighboring states: New Mexico, Colorado, Oklahoma and Louisiana (the sample has no companies headquartered in Arkansas), and exploiting the aforementioned home-biases using a dummy that equals 1 if companies are headquartered in Texas, interacted with a dummy variable taking on the value of zero through 1999 and one thereafter, as an instrumental variable. As a robustness check, we also use the fraction of investments across states made by VC firm headquartered in Texas before the shift, interacted with the 1999 dummy, as an alternative instrumental variable. The main advantage in using this policy shift as an exogenous shock to the capital available for VC firms instead of using ERISA as Kortum and Lerner (2000), is that the Texas constitutional amendment occurred when the VC industry was already established. The main disadvantage is that by restricting the sample to companies in Texas and its neighboring states, statistical power decreases.

We implement the instrumental variable estimator using two-stage least squares. In future versions of this work we may use a control function approach (e.g., Blundell and Powell (2004)) suitable for our non-linear count data models.

1.2 Results

1.2.1 The rate of innovative activity increases after VC investment

Table 1.3 contains the firs set of results where we measure the rate of innovative activity using yearly patent filings The table reports incidence rates. An incidence greater than one corresponds to a positive coefficien and a positive effect of the characteristic on patent production intensity. In column 1 the coefficien bigger than one on $After\ VC$ implies that there is an increase in patenting activity following VC investment. The interpretation of the coefficien is as follows: after a company is finance by a VC patent filing increase by 153.5% (e.g., from the mean of 0.37 filing a year to 0.57). In the second (third) column of Table 1.3 we repeat the analysis restricting the sample to VC investments after (prior to) 1999. Finally, column 4 restricts the sample to companies that file at least one patent before, and one patent after, the VC investment. Results are similar across the different subsamples.

In Panel B of Table 1.3, we divide the period after the VC investment into two: the period while the VC is an investor in the company, and the period when the VC exits the company. While we don't have information on the exact date on which VC firm exit their investments, we approximate the exit date as one year after the last observed financin round. As expected, the increase in patent applications is strongest while the VC is an investor in the company, and this result is robust to using the pre-1999 sample where the potential truncation of the fina years in the sample is reduced.

Table 1.4 examines the heterogeneity in the effect on patent filing following VC investment, and exit, across different industries. For industries that tend to use patents to protect Intellectual Property (IP) such as Biotech and Semiconductors, there is the largest increase in patent applications. Interestingly, Panel B shows how on average, part of the increase in patent filing persists after the VC exits the investment.

Table 1.5 breaks down results by type of VC exit.[9] Interestingly, for all types of VC exit patent production increases following the VC investment. As expected, however, for companies that go defunct, patent filing decrease dramatically after the VC leaves the company. This is also true for companies that get acquired. This last findin is presumably due to the fact that new patent filing for companies that are acquired are assigned to the buyer. Finally, the increase in patent applications is particularly pronounced for companies that ultimately go public. This is broadly consistent with recent finding by Bernstein (2012).

1.2.2 Unconditionally, the quality of innovative activity is not affected

Table 1.6 reports results from the Poisson formulation of patent quality. Panel A in Table 1.6 contains results from pooled regressions. The coefficien of 0.996 in column 1 implies that patents applied for after the VC investment garner 0.04% less citations than those file before venture funding (e.g., from the mean of 9.19 citation counts to 9.16). This effect is not economically or statistically significant The second and third columns replicate the analysis using as dependent variables: self-citations and non-self-citations, respectively. There is no significan change for either type of citation count.

Columns 4 through 6 in Panel A of Table 1.6 contain pooled regressions offsetting the different types of citation baselines in the estimation. The coefficien of 1.016 in column 5 implies that patents applied for after the VC investment garner 0.016% more citations than those applied for

[9]For some of the companies that SDC identifie as being involved in an active VC investment by 2009, the last recorded deal is very old (observations go back as far as 1979). We suspect that these observations are misclassifie as active investments. We check whether results are sensitive to this potential misclassification Reassuringly, we fin that overall results do not substantially vary whether we defin these investments as active or arbitrarily assume that they ended one year after the last recorded deal.

before the VC investment, and relative to the citation baseline. Similar to columns 1 through 3, the estimated coefficien is not economically or statistically significant

Panel B in Table 1.6 compares changes in citation counts while the VC is an investor in the company and after its approximated exit. Interestingly, patent quality seems to slightly increase following venture funding but invariably falls after the VC exit. The estimated effects are however, not statistically significant Finally, Panel C explores the dynamic pattern in venture funding and citation counts by restricting the sample to observations during which the VC is likely to still be an investor in the company.[10] We estimate Poisson models that use as independent variables indicators for the individual years of the patent filin relative to the year of the VC investment (event year 0 is the omitted base category with a coefficien normalized to one). Panel C in Table 1.6 shows no consistent pattern in the citation count for patents file around the VC investment, except for an apparent slight increase for event year 1, but which dies out in the following event year.

Table 1.7 examines the heterogeneity in the effect on the citation count following VC investment, and exit, across different industries. After controlling for the citation baseline, there is no evidence that innovation quality changes and this result is robust across industries.

Finally, Table 1.8 breaks down results by type of VC exit. There is a lot of variation in the estimated effect by type of VC exit. For companies that ultimately go public the citation count increases after the VC investment. This increase is also numerically true for companies that get acquired, although the effect is not statistically significant For companies that go public the increase in innovation quality disappears once the VC exits the company. This result is broadly consistent with Bernstein (2012). Interestingly, for companies that the SDC classifie as having an exit of type "Other" patent quality strongly decreases post VC exit. This effect is also true for companies that go defunct.

[10] In detail, an observation is only included if the application year of the patent is within one year of the company's last recorded VC investment.

1.2.3 Conditionally on the quality of companies, the quality of innovative activity decreases

Table 1.9 presents results from the Poisson formulation on patent quality that includes company fi ed-effects to control for the heterogeneity across companies. Interestingly, using this within-company estimator, the coefficien on $AfterVC$ is strongly significan and negative. The interpretation of the 0.719 coefficien in column 1 is that for a given company, patents file after the VC investment garner 29% less citations than patents file before the VC investment. The largest predicted decrease is on self-citations. Columns 4 through 6 repeat the analysis comparing the period after the VC investment and the period after the VC exit. The citation count is predicted to decrease both, after the VC investment and after the VC exit, although the decrease is signifi antly larger after the VC exit. Finally, Columns 7 and 8, present the dynamic pattern in citation counts around the VC investment. Consistent with VCs selecting companies with unusual patenting activity, the years before venture funding are associated with more significan patents. In contrast, the years after the VC investment are associated with consistently less important innovations.

Further, in unreported regressions we break down results by type of VC exit and by industry. We fin no interesting pattern for the estimated effect in either dimension.

In summary, the within-company estimator predicts a negative effect from venture funding on innovative quality. This negative effect is robust across all industries, and across all types of VC exit.

1.2.4 Conditionally on the quality of companies, the novelty of innovative activity decreases

Table 1.10 explores the relation between venture funding and the originality and generality of patents. Similar to the results for patent quality, we fin that unconditionally, the novelty and generality of companies' research output is not significantl affected by venture funding. However, conditional on company quality, VC has a strong and negative effect on both measures.

1.2.5 An attempt at controlling for endogeneity

As discussed above, one interpretation of the finding is that they simply reflec endogenous VC choices. For example, VCs may invest in companies when they expect a surge of patent filing following an innovative breakthrough. To test whether the finding are entirely explained by endogenous VC selection, in this section we consider and instrumental variable (IV) approach that exploits the policy shift in Texas explained in Section 2.

Table 1.11 reports the results for the IV analysis of the relation between venture funding and the rate of companies' innovative activity. The firs column reproduces the basic OLS results of regression model (3) that uses as dependent variable $\ln(Patents_{it}+1)$. Consistent with our Poisson regressions, patent filing increase following venture funding. The second column presents the corresponding reduced form, where we regress $\ln(Patents_{it}+1)$ against the instrument. There is a positive and significan relation.

In the second panel of column 3 in Table 1.11 we present the firs stage where we regress $AfterVC$ on the instrument. As expected, the instrument is positive and highly significant The F-test of the firs stage suggests the instrument is not weak (Stock and Yogo (2005)). The firs panel of column 3 presents estimates where we use 2SLS to deal with endogeneity. The $AfterVC$ dummy remains positive. Results are similar if we use as an instrument the fraction of investments made by VC firm across states interacted with the 1999 dummy as an instrumental variable.

Interestingly, the estimated effect of venture funding on patent filing using the 2SLS approach is higher than the biased OLS estimate. At face value, this result suggests that we are underestimating the positive effect of venture funding on the rate of companies' innovative activity by treating VC financin as exogenous. As is well known, however, IV estimates are only representative of the Local Average Treatment Effect (LATE) (i.e., the effect on companies who were finance because of the policy shift and that would not have been venture funded otherwise) and consequently, their interpretation is limited. The negative direction of the bias is consistent with the IV results from Kortum and Lerner (2000), and similar to other papers in the literature that use shocks to the availability of capital to VCs as an instrument for VC investment (e.g., Mollica and Zingales (2007) and Bernstein et al. (2008))

Because the variation in the instrument is at the regional level, standard errors in Table 1.11 are clustered at the state level. However, since the number of clusters is very small it is possible that estimated standard errors are biased downwards. In unreported results, we repeat the analysis clustering standard errors at the company level. Consistent with the presence of small-cluster bias, we fin that the estimated effect of venture funding on patent filing is no longer statistically significant

Table 1.12 reports results from the instrumental variable regressions for patent quality. Following the same structure as Table 1.12, the firs column reproduces the basic OLS results of regression model (5) using as dependent variable $\ln(Scaled\_Cites_{it}^{k}+1)$. Consistent with our Poisson regressions, patents file after venture funding have fewer citation counts. The second column presents the corresponding reduced form, where we regress $\ln(Scaled\_Cites_{it}^{k}+1)$ against the instrument. There is a negative and significan relation.

In the second panel of column 3 in Table 1.12 we present the firs stage where we regress $AfterVC$ on the instrument. Again as expected, the instrument is positive and highly significant The F-test of the firs stage suggests the instrument is not weak (Stock and Yogo (2005)). The firs panel of column 3 reports of the 2SLS model that deals with endogeneity of VC investments. The $AfterVC$ dummy remains negative with a coefficien that is much larger in absolute value than the one in column 1. This result suggests that the negative relation between venture funding and patent quality is unlikely to only arise from endogenous selection.

Similar to Table 1.11, standard errors in Table 1.12 are clustered at the state level. In unreported results we check for the presence of small-cluster bias and cluster standard errors at the company level. Results in Table 1.12 are robust to this alternative type of clustering.

1.3 Conclusions

Given the increasing popularity of growth policies that encourage VC activity (e.g., Lerner (2009)), it is of paramount importance to understand the effect of VC on the innovative activity of companies. This chapter tries to do so using a sample of US-based startups firs finance by VCs during 1976 through 2008, and examining the changes after venture funding in the companies' propensity to patent, as well as in the quality of companies' innovations.

Contrary to existing research on European-based VC-backed companies, we fin that the scale of companies' innovative activity significantl increases after venture funding. Interestingly, we also fin that the type of innovations produced by companies is affected by the VC investment. Mainly, VC is associated with a decrease in the quality and novelty of companies' research output. To address natural concerns about endogeneity, we exploit a policy shift in Texas that freed public pension funds to invest in VC. Our results suggest that the association between venture funding and companies' rate and quality of innovative activity may not simply arise from endogenous selection.

There are several interpretations of our findings The negative relation between VC and patent quality is consistent with companies exerting more effort on the development part of R&D, relative to research, after venture funding. It is likely that during the transition towards commercialization, the patents file by companies correspond to more marginal inventions. This interpretation is broadly consistent with Hellmann and Puri (2002), who fin that VC is associated with a significant reduction in the time to bring a product to market. Also, patent filing can increase after venture funding if VCs encourage their companies to build up their patent portfolios to better protect themselves from future patent wars against competitors.

There are many directions this future research could take. One interesting follow-up question is to explore the mechanisms through which venture funding affects companies' research output. In future versions of the work we may pursue this line of research. Finally, one potentially important omission is the impact of VC financin on patent trade. Patent trade remains a relatively unexplored area of research, and VCs are likely to encourage their companies to strategically manage their patent portfolios as a short-term source of profits This topic looks like a particularly promising area of research for future studies.

2 Venture Capital and the Diffusion of Knowledge

Does the diffusion of knowledge depend on the environment in which ideas are developed? This chapter explores this question by examining how the diffusion of an idea is affected by Venture Capital (VC) financin of the company that patented the idea. Venture Capitalists (VCs) invest in privately held innovative business. In addition to providing capital, they are generally believed to contribute value in other ways (e.g., Hellman and Puri (2000) and Hellman and Puri (2002)). In this chapter, I show that VC financin has a positive, causal effect on the diffusion of patented knowledge. The empirical evidence points to two mechanisms: VCs facilitate communication among companies in their portfolios, and more broadly, VC financin appears to certify the value of innovations to the general public.

I use patent citations to measure knowledge diffusion (e.g., Jaffe (1986), Hall et al. (2001) and Jaffe and Trajtenberg (2002)). Legislation requires inventors to cite all previous patents that their inventions build upon. Subject to caveats, discussed below, these citations are an indirect measure of knowledge linkages between innovations (Hall et al. (2001)). To distinguish the effect of VC financin on knowledge diffusion from its effect on knowledge production, I study a sample of patents invented in companies before they are VC financed I compare subsequent increases in citations to these patents to the citations of comparable patents in the same technology-class and vintage-year, and not invented in VC-backed companies. The comparison focuses on knowledge diffusion outside company boundaries, and only includes citations from inventors outside the patenting company. My firs findin is that after VC financin citations to a given patent increase by 19% relative to the citations of comparable patents.

The firs findin suggests that the diffusion of already existing, disclosed ideas increases with VC ownership. While this result is interesting, one concern is the endogeneity of VC investments. For instance, VCs may anticipate which existing innovations will be cited in the future. Alternatively, VC financin may increase awareness of innovations and affect future citations. To isolate the causal effect, I use time-series variation in the assets of state public pension funds as an instrumental variable (IV) (Mollica and Zingales (2007)). This IV approach relies on the home-bias of state pension funds in their VC investments (Hochberg and Rauh (2012)), and on the exclusion restriction that changes in pension assets are independent of the innovation opportunities facing the companies. One potential concern with this exclusion restriction is that unobserved economic activity at the state level may affect both the size of state pension funds and the innovative opportunities of local companies. Since the analysis compares citations to patents file by VC-backed companies to those of comparable patents, the exclusion restriction is satisfied as long as the effect of unobserved economic activity on innovation opportunities within a state is uniform across local patents in the same technology-class and vintage-year.[11] As a robustness check, I relax this identificatio assumption by eliminating citations directly linked to local innovation opportunities and only counting citations from inventors in states other than the home-state of the patent. Using this IV approach, I fin evidence that the effect of VC financin on patent citations is causal.

The second part of this chapter explores some mechanisms driving the effect of VC financin on patent citations. One potential mechanism behind this effect is that VC financin increases awareness of companies' innovations, possibly certifie their value, and spurs follow-on innovation by other inventors. In addition, VCs may also facilitate communication among companies in their portfolio, and facilitate diffusion of knowledge in their networks. To test these mechanisms, I distinguish between two types of citations: those from inventors in companies finance by the same VC, portfolio-linked, and those from all other unrelated inventors, non-portfolio-linked. Consistent with the firs mechanism, I fin a causal increase in non-portfolio-linked citations. Consistent with the second mechanism, I fin that the increase in portfolio-linked citations is four times stronger than the increase in non-portfolio-linked citations. I also analyze inventor mobility and patent sales around the financin event as potential channels behind the effect of VC on patent citations.

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[11] For example, it assumes that natural gas shale discoveries affect citations to all Hydraulic Fracture patents file in 1995 and developed in California in a similar manner.

Inventors may choose to move to other companies after VC financing for example, if the presence of VC investors implies a transition from creative freedom to a commercial focus (e.g., Aghion et al. (2008)). This inventor mobility can facilitate knowledge fl ws between inventors' new and old employers. Also, companies may sell patents outside their core areas after VC financin and directly transfer knowledge to buyers. My finding suggest, however, that the effect of VC on patent citations is not driven by either of these two mechanisms.

The last part of this chapter addresses concerns about the relationship between the dependent variable in the analyses, patent citations, and what I really want to measure, knowledge diffusion. For example, patent reviewers are also likely to become aware of a company after it is VC financed. Since citations from patent reviewers are included in the analysis, citations may increase when there is no diffusion of knowledge. I test this alternative story using a sub-sample of patents for which I can distinguish the citations added by patent reviewers and exclude those from the analysis. Results remain qualitatively similar, which minimizes concerns regarding the interpretation of patent citations as knowledge fl ws. I consider and test other alternative stories.

This chapter contributes to the literature that relates the diffusion of innovation to the institutional environment in which new technology is developed (e.g., Mokyr (2003), Gans et al. (2010), Williams (2011) and Gans and Murray (2012)). I extend this literature by focusing on the diffusion of already patented innovation and showing that conditional on disclosure VC ownership matters for diffusion.

This chapter also relates to the literature that considers the role of VC on innovation (e.g., Kortum and Lerner (2000), Hirukawa and Ueda (2008) and Nanda and Rhodes-Kropf, (2011)). I offer a new approach to investigate this question by using data at the patent level and by focusing on knowledge diffusion. A back-of-the-envelope calculation based on the finding suggests that by facilitating the diffusion of their companies' patents, VCs have contributed 2% to 10% of patent production in the U.S. This findin helps explain why researchers using industry-level data estimate that VCs contribute to 14% of patent production (Kortum and Lerner (2000)) even though less than 4% of patents have been assigned to VC-backed companies.[12] I argue that at least part of this difference can be attributed to knowledge spillovers generated by VCs.

Finally, the chapter also relates to the literature that explores non-financia services VCs provide to their companies. Previously documented mechanisms include recruiting key managers (Hellmann and Puri (2002)), implementing strong governance mechanisms (Hochberg (2011)), and facilitating strategic alliances (Lindsey (2008)). I fin evidence that VCs help diffuse knowledge across companies in their portfolio. Consistent with Hellmann (2002), my finding suggests that VC portfolios change the complementary assets available to companies. Since patent citations have been shown to be associated with value (Hall et. al (2005)), this non-financia service of VCs can have value implications for VC-backed companies.

The rest of this chapter is organized as follows. Section 2.1 explains the data sources used to construct the sample and presents summary statistics. In Section 2.2, I discuss the empirical strategy used to identify the effect of VC on knowledge diffusion and present results. Section 2.3 explores the mechanisms behind this effect. Section 2.4 discusses the interpretation of patent citations as a measure of knowledge fl ws, and considers alternative interpretations. Section 2.5 concludes.

2.1 Data Description and Summary Statistics

The data on VC investments are from SDC's VentureXpert. Companies headquartered in the United States (U.S.) and finance by U.S.-based VC firm from 1976 to 2008 are identified Data on patents comes from the Harvard Business School (HBS) patent database (Lai et al. (2009)), which has information on U.S. patent assignments from January 1976 through December 2008 based on the records from the U.S. Patent and Trademark Offic (USPTO). I combine the two data

[12]See Appendix.

sources by searching for each of the VC-backed company names among the patent assignees. The Appendix has a detailed account of the matching procedure and includes summary statistics for the matched sample.

To distinguish the effect of VC financin on knowledge diffusion from its effect on knowledge production, this chapter restricts the data to patents file by companies at least two years before they are f nanced by a VC.[13] Since the empirical strategy explores subsequent changes in citations to these patents, I only consider companies that were finance by VCs between 1977 and 2003. This restriction makes sure that I observe at least two years of citations before VC f nancing, and f ve years of citations afterwards. After these restrictions, the analysis sample consists of 2,336 patents file by 752 companies.

Table 2.1 presents summary statistics of the analysis sample and explores its representativeness of all patents that are assigned to VC-backed companies, and of all companies finance by VCs. Panel B shows that the analysis sample is slightly more concentrated in Massachusetts, Pennsylvania, and Texas (Panel B). Also, the sample is composed of relatively more mature (Panel C) and successful (Panel D) companies from industries that rely on patents to protect their Intellectual Property (IP), such as medical health and semiconductors (Panel E).

Using these patents, I construct a database at the patent-year level where the variable of interest is the annual number of citations received by patents from the patent's application year until 2008. Since the analysis focuses on knowledge diffusion outside company boundaries, I only include citations from inventors outside the patenting company. Panel G of Table 2.1 shows summary statistics of annual citations. Consistent with the well-known skewness in patent citation data,

[13] There are two dates associated to patents that are relevant for this study: the application-year and the grant-year. The application-year corresponds to the year in which inventors fil their patents at the USPTO. The grant year corresponds to the year in which the USTPO grants the patent to the inventor. The lag between these two dates is on average 2 years, and is not is not statistically different for patents invented by companies with and without VC-investors. In unreported results I restrict the sample to patents granted at least two years before they are finance by a VC. Results are robust to this change.

mean and median annual citations are 0.92 and 0, respectively. Citations are also classifie by state using data on the geographical location of the citing inventors. Panel G shows summary statistics of out-of-state citations, which exclude citations from inventors in the home-state of the companies that file the patents.

2.1.1 Citation baseline

Patent citation rates have been increasing over time and tend to vary according to technology-class and vintage-year (Hall et al. (2001)). To control for these aggregate trends in citations, and for patent life-cycle effects in the analysis, I defin a set of comparable patents as follows. For every patent in my sample I determine all U.S. patents assigned to the same USPTO technology-class,[14] with the same application-year,[15] and that were not file by a VC-backed company.

Using the comparable patents, I construct an annual citation baseline as:

$$b_t = \frac{Total\ Cites_t}{Number\ of\ Comparable\ Patents}, \tag{6}$$

where $Total\ Cites_t$ corresponds to citations received by comparable patents at time t. Panel G in Table 2.1 reports summary statistics of the citation baseline. On average, the patents invented in VC-backed companies receive 0.32 more annual citations than comparable patents. Panel G in Table 2.1 also reports summary statistics of a citation baseline at the state level, in which the comparable patents are additionally restricted to have been invented in the home-state of the VC-

[14] At present, the USPTO has assigned more than 400 technology-classes, examples of which include Radio Wave Antennas and Wheel Substitutes for Land Vehicles.

[15] In unreported results I use the grant-year as vintage-year, and also, both the application-year and the grant-year, to construct the group of comparable patents. Results remain robust to these alternative definitions Following Hall et al (2001), however, I use application-year to avoid including in the estimation noise from the review process at the USPTO.

backed company that file the corresponding sample patent.

2.1.2 Restricted Sample

I collect information on financia assets held by state and local public pension funds from the State and Local Government Public-Employee Retirement Systems annual survey. This survey is conducted by the Census Bureau and is available starting in 1993. The 1993 to 2008 period is referred to as the restricted sample throughout, and corresponds to the sample used in the IV analysis of Section 2.2.3.

Table 2.2 reports summary statistics on the restricted sample, which consists of 1,657 patents file by 517 VC-backed companies. Panel B in Table 2.2. reports the value of the assets held by local and state public pension funds deflate by the Producer Price Index (PPI) and expressed in billions of 1982 U.S. dollars. Panels B, C, D, and E show that the restricted sample is fairly representative of the analysis sample. The main difference is that the restricted sample is slightly overrepresented in Early Stage and Biotech companies. Finally, Panel G in Table 2.2 reports descriptive statistics for the restricted sample on the main variables in the analysis: annual citations to patents, the annual citation baseline, and the annual citation baseline at the state level. Compared to the analysis sample, average annual citations to patents increase for the restricted sample, reflectin the overall increase in citations throughout the period.

2.2 Empirical Analysis

2.2.1 Univariate Tests

Table 2.3 presents preliminary evidence that citations to patents increase after companies are VC financed On average, patents are cited 0.64 times a year before venture funding. After VC financing however, average annual citations increase by 63% to 1.04. This percentage increase is summarized by the Ratio of 1.63 reported in Table 2.3. The average annual citation baseline also increases, which illustrates aggregate citation trends. After controlling for these trends, the estimated percentage increase in citations decreases from 63% to 33%. This adjusted percentage increase is summarized by the Ratio of Ratios of 1.33 reported in Table 2.3.

Table 2.3 also shows that even before VC financin annual citations to patents are on average significantl higher than the citation baseline. This difference does not invalidate the use of the citation baseline to control for aggregate trends in citations at the technology-class and vintage-year level. The key assumption is that citation trends, and not necessarily the levels, would be similar across the patents in my sample and comparable patents in the absence of VC financing I return to this assumption in the next section.

2.2.2 Poisson Regressions

Citation data are non-negative and discrete, thus, I use a Poisson model, which is the standard model for count data (Cameron and Trivedi, 1998).[16] I estimate the following equation:

$$E\left[Cites_{pt}|VC_{pt},b_t\right] = \exp\left(\alpha_p + \ln(b_t) + \beta VC_{pt}\right), \tag{7}$$

where the expected number of citations received by patent p in year t, $Cites_{pt}$, is an exponential function of a dummy variable, VC_{pt}, which equals one after VC financing I include a full set of patent fi ed effects in the estimation, α_p, which absorb all time-invariant patent heterogeneity. To control for aggregate trends in citations, I offset the citation baseline, b_t, in the estimation. This is implemented by including in the Poisson regression the logarithm of b_t with a coefficien fi ed

[16] Another common model for count data is the Negative Binomial model which is a generalization of the Poisson model that addresses overdispersion by including an additional error term to capture unobserved factors. In unreported analyses I replicate the analsysis using this model. Results hold and are not statistically different across models.

to one.[17] To understand the intuition behind this approach, note that in equation (7) the expected number of citations received by patents absent VC financing and ignoring the patent fi ed effects, equals the citation baseline.

Table 2.4 reports the results from the Poisson analysis where I cluster standard errors at the company level. All reported coefficient are incidence rates and reflec the proportional increase of annual citations to an increase in the explanatory variable. An incidence rate greater than one corresponds to a positive effect of the explanatory variable on annual citations to patents. An incidence rate below one corresponds to a negative effect. Correspondingly, indications of statistical significanc do not reflec whether the coefficient are different from zero, as is usual, but rather whether they differ from one.

Column 1 in Table 2.4 reports the results from a pooled Poisson regression of equation (7) excluding the citation baseline. I estimate the model using maximum likelihood (MLE). The interpretation of the coefficien for VC_{pt} is that annual citations to patents increase 62.7% after VC financing Note the correspondence between the estimated coefficien and the Ratio reported in Table 2.3.[18]

Column 2 in Table 2.4 summarizes the results from a pooled Poisson regression of equation (2) by MLE. After controlling for aggregate trends, the estimated increase in citations declines. The interpretation of the coefficien for VC_{pt} in Column 2 is as follows: after VC financing annual citations to patents increase 34.6% in excess of the citation baseline. Note the correspondence

[17] The baseline removes any aggregate annual variation. This technique is similar to including time-fi ed effects (cross technology-class and vintage-year) in the estimation.

[18] The estimated constant in Column 1 of Table 2.4, corresponds to the average annual citations to patents before VC financin reported in Table 2.3.

between the estimate in Column 2 and the Ratio of Ratios reported in Table 2.3.[19]

Column 3 in Table 2.4 presents results from the fi ed effects Poisson model. One concern in using fi ed effects in non-linear models is that estimates may be inconsistent because of the incidental parameters problem.[20] I follow the literature and estimate the model using conditional quasi-maximum likelihood (QMLE) as developed by Hausman et al. (1984), which eliminates the patent fi ed effects by conditioning on $\sum Cites_{pt}$ (a sufficien statistic of α_p).[21] The interpretation of the coefficien for VC_{pt} is that annual citations to the same patent, in excess of the citation baseline, increase by 18.9% after VC financin of the issuing company.

In unreported results, I repeat the analysis of Table 2.4 excluding California, Massachusetts, and Texas, and restricting the sample to the pre- and post-dot-com periods. The effect is not statistically different across sub-samples. I also examine the heterogeneity of the results by patent age. I fin that the increase is highest for patents younger than f ve years, but the effect is also positive and signifi ant for patents between f ve and ten years of age. In addition, I explore the heterogeneity of results by VC skill as measured by the number of prior successful financin rounds. I fin that more experienced VCs have a greater effect on citations, but this stronger effect is not statistically significant I distinguish between the extensive and intensive margins. I fin that conditional on having been cited before VC financing the increase in citations to patents is

[19] The constant in Column 2 corresponds to the ratio between average annual citations to patents and the average citation baseline before VC financin reported in Table 2.3.

[20] The fi ed-effects Poisson model, however, is one of the few models for which consistency of the MLE holds despite the presence of incidental parameters (Cameron and Trivedi (1998)).

[21] The Poisson model is in the linear exponential family and the coefficien estimates remain consistent as long as the conditional mean is correctly specifie (Wooldridge (1999)). In the estimation, therefore, I do not assume that the mean and the variance are equal, or arbitrary independence across observations. Instead, I compute the variance-covariance matrix using the outer product of the gradient vector and clustering the standard errors at the company level.

not statistically significant In contrast, for patents with no prior citations, the effect is large and significant Furthermore, I experiment with different definition of the baseline by excluding from the set of comparable patents those that are never cited throughout the sample, those that originate in large companies, universities, and the public sector, [22] and by adding geographical restrictions using the citation baseline at the state level define in Section 2.1.1. Results are quantitatively similar across the different versions of the baseline.[23] Finally, I also explore the effect of VCs on the dispersion of citations across technology classes (i.e., the generality measure of Hall et al. (2001)), and fin no significan effect.

Figure 2.1 explores the dynamics of the effect uncovered in Column 3 of Table 2.4. I estimate a fi ed effects Poisson model where the independent variables are indicators for individual years relative to the year of VC financing and restricting observations to two years before, and f ve years after, the VC financin event (Event-year 0 is omitted from the estimation to avoid multicollinearity with the patent fi ed-effect). Figure 2.1 plots the estimated coefficient (solid line) together with their 95% confidenc interval (dashed lines). Before VC financing citations to the same patent in excess of the baseline are not statistically different from those in the year of VC financing This pattern is reflecte in the estimated coefficient of the dummy variables indicating event-years pre VC financing neither is statistically different from one. This result is reassuring, as it shows that the subsequent increase in citations is not driven by a pre-existing trend in citations. In contrast, the estimated coefficient of the dummy variables indicating event-years post VC financin are all larger than one, and significan from event-year 2 onwards. Note that although not significant the point estimates for the dummy variables indicating event-years pre VC financin are actually negative, which suggests that the patents in the sample were relatively unknown before the issuing

[22] I thank Scott Stern for this suggestion.

[23] In future versions of the paper I may report main results using more restrictive baselines as precision generally increases.

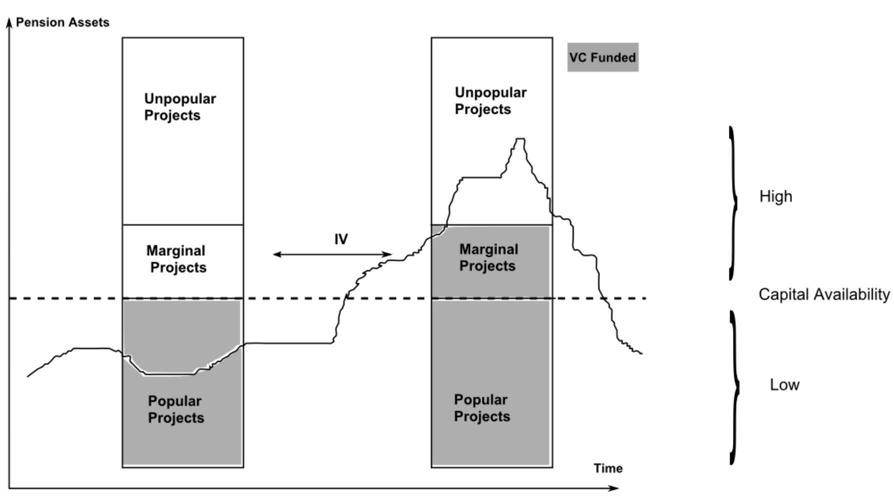
companies are finance by a VC. This pattern is consistent with the aforementioned results on the extensive and intensive margins.

One interpretation of the temporal patterns in Figure 2.1 is that since there is no pre-trend, the increase in citations reflect the causal effect of VC financing Alternatively, VCs may be able to anticipate which innovations are more likely to be dominant in the future, and the increase in citations at least partially reflect VCs' ability to time their investments. Regardless of the interpretation, and given that citations are associated with value (Hall et al. (2005)), the results help visualize why VCs can command high compensation schemes. Even if the increase in citations only reflect the skill of VCs in timing their investments, this is interesting from a financia perspective, as it means that VCs can cherry pick projects before any other agent in the market. This ability to pick projects is not easy to imitate, and consequently translates into high returns. From the point of view of policy, however, it is important to disentangle the two interpretations because the policy implications are very different.

2.2.3 Addressing endogeneity of VC investments

To isolate the causal effect, I use time series variation in the assets of state public pension funds as an instrumental variable (IV) (Mollica and Zingales (2007)). This IV approach relies on the home-bias of state pension funds in their VC investments (Hochberg and Rauh (2012)), and on the exclusion restriction that changes in pension assets are independent of the innovation opportunities facing the companies. One concern with this exclusion restriction is that unobserved economic activity may affect both pension assets and companies' innovation opportunities. Since the analysis compares citations to patents file by VC-backed companies to those of comparable patents, the main identificatio assumption is that the effect of unobserved economic activity on innovation opportunities within a state is uniform across local patents in the same technology-class and vintage-year. In this section, I explain the IV approach in detail.

Intuition The intuition behind the IV approach is best explained following the same logic as the local average treatment effect (LATE) of the linear literature (Imbens and Angrist (1994)). Start by assuming that VCs select which companies to financ based on the unobserved and heterogenous future popularity of their patents. Every year companies are classifie into three classes: popular, marginal, and unpopular. Popular (unpopular) companies are those for which the future popularity of their patents is high (low) and will (will not) be funded irrespective of the availability of capital for VCs. Marginal companies, with marginal patents of average popularity, are funded only if the availability of capital for VCs is sufficientl high. For simplicity, assume that every period the availability of capital for VCs can be either high or low. If there is high availability of capital, VCs financ their marginal companies, otherwise, marginal companies are not funded. The IV approach is equivalent to comparing the average outcome (in terms of citations) for marginal patents across periods of high and low availability of capital for VCs. The figur below illustrates the example.



This example helps clarify common misconceptions of IV. For instance, the estimation strategy does not assume that given high capital availability VCs randomly pick the companies they finance Instead, the identificatio strategy relies on two assumptions. First, that the size of state pension assets is indicative of the local availability of capital for VCs. Second, that the average quality of companies (and their patents) faced by VCs within a state is comparable across periods of high and low pension assets. In the next sections, I discuss these two assumptions in detail.

State pension assets and local investments by domestic VC firm The validity of the firs identificatio assumption stems from the home-bias of state pension funds in their VC investments, and the home-bias of VCs in their financin of portfolio companies. Hochberg and Rauh (2012) show that public pension funds display a 23 percentage point home-state overweighting in VC investments. On the home-bias of VC financing there is abundant evidence (e.g., Lerner (1995), Cumming and Dai, (2013)). To provide additional suggestive evidence, I collect information from VentureXpert on total value of investments by VC firm (both inside and outside their home-state) and estimate the following equation:

$$Investment_{st} = \alpha + \theta_s + \gamma_t + \beta Pension_{st-1} + \eta_{st}, \quad (8)$$

where $Investment_{st}$ is the value of investments by VCs headquartered in state s at year t (deflate by PPI). $Pension_{st-1}$ corresponds to the assets of local and state public pension funds in state s, deflate by the PPI and lagged by one year.[24] I include in the estimation state fi ed effects, θ_s, which control for the time-invariant importance of VC investments in states. I also include time fi ed effects, γ_t, which control for aggregate trends.

Table 2.5 summarizes results from estimating equation (8) and clustering standard errors at the state level. The interpretation of the coefficien in Column 1 is as follows: an increase of $1 billion in state pension assets increases the value of VC investments by $52 million. The second (third) column uses as the dependent variable the value of investments by VCs in local (non-local) companies. The interpretation of the coefficien in the second (third) column is as follows: an increase of $1 billion in state pension assets increases the value of VC investments in local (non-

[24] The process for VCs of raising a fund and beginning to deploy capital takes about one to two years.

local) companies by \$36 (\$16) million. Columns 4 through 6 replicate the analysis of Columns 1 through 3 restricting the dependent variable to VC financin of *new* companies. The results are robust to this restriction. Overall, results in Table 2.5 show that the size of state pension assets affects the availability of capital for VCs.

Local innovation opportunities and public pension assets The second identificatio assumption is the exclusion restriction and cannot be tested.[25] To examine its validity, consider the three main sources of variation in the size of state pension assets: demographic conditions, pension policy, and returns to past investments. The fir t two are determined by broader socioeconomic considerations other than current innovation opportunities and are unlikely to raise any concerns. Returns to past investments, however, may reflec unobserved economic activity at the state level that can affect both the size of state pension funds and the innovative opportunities of local companies. Since for every patent file by a VC-backed company the citation baseline includes citations to comparable patents not necessarily invented in the same state, changes in innovation opportunities within a VC-backed company's state may affect disproportionately citations received by the company's patents relative to the citation baseline. This disproportional effect could imply that the average quality of patents faced by VCs, as measured by citations in excess of the baseline, across periods of high and low pension assets is not comparable. This lack of comparability would raise concerns regarding the exclusion restriction.

To address this concern, I use the citation baseline at the state level define in Section 2.1.1. The identificatio assumption is that the effect of unobserved economic activity on innovation opportunities within a state is uniform across local patents in the same technology-class and vintage-year. As an additional robustness check, I relax this identificatio assumption by eliminating citations

[25] As suggestive evidence, in unreported regressions I ran a placebo test where I test whether the correlation between pension assets and relative citations to patents in the sample is significan for all periods during the life of a patent. Reassuringly, I fin that the correlation is only significan while the VC is an investor in the company.

directly linked to local innovation opportunities and only counting citations from inventors in states other than the home-state of the patent (out-of-state citations).[26]

Econometric Considerations I now turn to a rigorous econometric treatment of the IV approach. I start by noting that to estimate the fi ed effects Poisson model using IV one may think to follow the conventional approach in the linear literature. Regress the endogenous variable VC_{pt} against the instrument and the patent fi ed effects, and use the predicted value from that regression as a regressor in the fi ed effects Poisson model instead of VC_{pt}.[27] This approach, however, is not valid because the expected value operator does not pass through non-linear functions. Instead, to estimate the non-linear IV I follow Wooldridge (1997) and Windmeijer (2000) and use a quasi-differentiation of the fi ed effects Poisson model, together with the implied exclusion restriction of the IV, to derive moment conditions, which I estimate using the generalized method of moments (GMM-IV hereafter).

The main intuition behind this approach is as follows. Recall from Section 2.1 that although the fi ed effects Poisson model does not suffer from the incidental parameters problem, the fi ed effects are still eliminated for convenience in the estimation. In this sub-section, I follow the same principle using an approach similar to the within transformation in the linear literature. The starting point is the fi ed effects Poisson equation (7). To simplify, let $\mathbf{x}_{pt} \equiv [\ln(b_t)\ VC_{pt}]'$ and $\mathbf{B} \equiv [1\ \beta]$, and consider the following transformation that eliminates α_p as suggested by Wooldridge (1997):

$$\frac{Cites_{pt}}{\exp\left[\mathbf{x}_{pt}\mathbf{B}\right]} - \frac{Cites_{pt+1}}{\exp\left[\mathbf{x}_{pt+1}\mathbf{B}\right]} = \alpha_p\left(\varepsilon_{pt} - \varepsilon_{pt+1}\right) \tag{9}$$

[26] See Table 1 Panel G for summary statistics on out-of-state citations.

[27] This is an example of the so-called forbidden regressions.

Let $Pension_t$ correspond to the assets of local and state public pension funds at year t in the home-state of the company that file patent p. Combining equation (9) with the exclusion restriction, i.e., $E\left[\varepsilon_{pt}|Pension_t,...,Pension_1,b_t,\alpha_p\right]=1$, gives the following moment conditions:

$$E\left[\frac{Cites_{pt}}{\exp\left[\mathbf{x}_{pt}\mathbf{B}\right]}-\frac{Cites_{pt+1}}{\exp\left[\mathbf{x}_{pt+1}\mathbf{B}\right]}\mid Pension_{t-1},b_t\right]=0. \tag{10}$$

Using the moment conditions (10) generally causes computation problems. For example, when the regressors include dummy variables such that the moment conditions can be made close enough to zero by choosing arbitrarily large βs. To address this concern, I follow Windmeijer (2002), and multiply through by $\exp(\mu_x\beta)$, where $\mu_x=(NT)^{-1}\sum\sum\mathbf{x}_{pt}$. This adjustment minimizes the computational problem because the deviated variables (i.e., $\mathbf{x}_{pt}-\mu_x$) will always take on positive and negative values. The modifie moment conditions I estimate to calculate the GMM-IV estimator are the following:

$$E\left[\frac{Cites_{pt}}{\exp\left[\left(\mathbf{x}_{pt}-\mu_x\right)\mathbf{B}\right]}-\frac{Cites_{pt+1}}{\exp\left[\left(\mathbf{x}_{pt+1}-\mu_x\right)\mathbf{B}\right]}\mid Pension_{t-1},b_t\right]=0. \tag{11}$$

IV results Table 2.6 presents the basic IV results. I begin by providing the fi ed effects Poisson estimates using the restricted sample of the GMM-IV approach in Column 1.[28] The estimated coefficien remains positive and statistically significant The GMM-IV estimator that uses $Pension_{t-1}$ to instrument for VC_{pt} is reported in Column 2. A comparison between Columns 1 and 2 reveals that the estimated effect increases from 17.1% to 49.5% after accounting for non-random timing of VC investments.

Table 2.6 also reports results using a standard linear IV approach (2SLS). As the dependent

[28] Recall that the data on state pension assets is only available at the Census starting on 1993. For details, see Section 2.1.2.

variable, I use scaled citations define as the ratio between citations to patents and the citation baseline. As shown in Columns 5 and 6, the results are similar across the non-linear and the linear approaches. The second panel in Column 6 reports results from the first-stage where I regress the endogenous variable, VC_{pt}, on the instrument and on patent fi ed effects. The F-statistic suggests that the instrument is unlikely to be weak (Stock and Yogo (2005)).[29]

Tables 2.7 and 2.8 present the IV approach using the citation baseline at the state level. Table 2.8 summarizes results of the main robustness check where I use out-of-state citations as the dependent variable to minimize concerns that unobserved economic activity may affect both VC financin and patent citations. I report standard errors clustered at the company-level as they are more conservative than those at the state level, which is suggestive of small-cluster bias. Tables 2.7 and 2.8 show that the results continue to hold and are quantitatively similar to the basic IV results in Table 2.6.[30][31]

As extra robustness checks, Tables 2.6 through 2.8 report results using alternative instruments. In each of these tables, the third (seventh) column reports estimates using $Pension_{t-1}$ normalized by average state GDP (*Pension_Norm*) as instrument and using the GMM-IV (2SLS) approach. Similarly, the fourth (eight) column reports estimates using $Pension_{t-1}$ demeaned at the time-level (Δ*Pension*) as instrument and using the GMM-IV (2SLS) approach. The results from this

[29]The correlation in-sample between the endogenous variable and the instrument is 0.18 and is statistically signifi cant at the 1% level.

[30]However, note that the interpretation of the results changes. To illustrate, the coefficien of Column 1 in Table 2.8 is interpreted as follows: after companies are finance by a VC, out-state citations to the same patent increase by 24.7%, relative to other patents in the same technology-class and vintage-year and issued in the same state.

[31]Note that the difference in observations from Tables 2.6, 2.7, and 2.8, is due to the fact that by restricting the dependent variable to out-state citations or/and definin relative citations at the state level, there are patents for which there is not enough variation for the fi ed-effects Poisson to be estimated. Consequently, comparisons across models do not have a straightforward interpretation.

robustness checks are qualitatively similar to the main results.

In additional unreported regressions, I exclude California from the sample and results remain are qualitatively similar. I also experiment with different versions of the baseline by excluding from the matching patents the patents that originate in large companies and the patents that are never cited throughout the sample. I also sharpen identificatio by definin the citation baseline at the city level.[32] Results are quantitatively similar across the different versions of the citation baseline, and significanc improves in most cases.[33] In conclusion, the effect of VC financin on patent citations is always positive, and significan across most IV specifications

2.2.4 Interpretation of results

An interesting findin that emerges from Tables 2.6 through 2.8 is that the IV estimates always numerically exceed their basic (Poisson and OLS) counterparts. If one assumes on a priori grounds that the basic approach leads to upward-biased estimates of the true causal effect of VCs, the even larger IV estimates present something of a puzzle. This puzzling result is common to all papers in the VC literature that instrument VC investments using changes in the availability of capital for VCs (e.g., Kortum and Lerner (2000), Mollica and Zingales (2007), and Bernstein et al. (2010) for the PE case).[34] Does this mean that VCs have no skill in selecting companies and that the increase in citations corresponds to the average treatment effect (ATE)? Not necessarily, because

[32] I thank Amit Seru for this suggestion.

[33] When I defin the citation baseline at the city level, I lose a lot of observations, thus the power in these regressions is reduced. In future versions of this paper, I may use one of these alternative versions of the baseline as the preferred set of results.

[34] These results echo the debate in the literature of the returns to schooling, particularly the papers by (Card (1994) and Card (2001)).

identificatio using IV is representative only of the marginal patents whose treatment is affected by the instrument (as illustrated in the figur of Section 2.2.3), and which are not necessarily representative of the general population of patents. This is the standard argument of LATE in the linear literature (e.g., Imbens and Angrist (1994)).

One interpretation is that there is underlying heterogeneity in the effect of VC financing and changes in the capital available for VCs trigger investments on a sub-population of patents whose diffusion is particularly responsive to VC financing For example, if the abundance of capital allows VCs to experiment more effectively and shifts the types of startups that they financ towards those that are riskier and more innovative. To explore this idea, I compare the average novelty of patents from companies finance across periods of high and low availability of capital for VCs, as determined by pension assets. A company is define to have been finance in a hot (cold) market, if pension assets in the home-state of the company during the year of the VC investment are within the top (bottom) 25% of the sample. As a proxy for novelty, for each patent I construct the "originality" measure of Hall et al. (2001) as one minus the Herfindah index of the cited patents across technology-classes.[35] The intuition is that patents that combine existing knowledge from few technology-classes to create something new (and useful) probably constitute more marginal improvements relative to patents that combine more different ideas ex-ante.

Table 2.9 shows that patents funded in hot markets are on average more original than those funded in cold markets.[36] The difference is statistically significant even after controlling for the

[35] I use both standard and adjusted originality measures. The latter is based on the bias-correction described in Jaffe and Trajtenberg (2002).

[36] Graphically, Table 2.9 compares the shaded regions of the rectangles in the Figure of Section 2.2.3 across periods of high and low pension assets. The exercise of Table 2.9, therefore, provides suggestive descriptive evidence of the characteristics of marginal patents. A common misconception is that this findin contradicts the exclusion restriction. This is not the case. Note that the exclusion restriction is *not conditional* on VC financing and compares the average quality of patents across periods of high and low pension assets. Graphically it compares the full rectangles, including both shaded and un-shaded regions of the rectangles.

average originality of matching patents. This suggestive evidence is in line with Hirukawa and Ueda (2008) and Nanda and Rhodes-Kropf (2011), and suggests that VCs play an additional role on innovation. Not only do VCs financ the innovation of their portfolio companies and facilitate the diffusion of knowledge, they also seem to use available capital to experiment, a role that is arguably needed for the commercialization and diffusion of novel technologies (Nanda and Rhodes-Kropf (2011)).

As it is common of IV analyses, one issue that remains to extrapolate policy lessons regards the external validity of the results. To inform policy, however, the ATE may be less relevant than the average return for the group who will be impacted by a proposed reform (Imbens (2009)). Since an important part of growth policies seek to stimulate VC financin via shocks to the capital that is available for VCs (Lerner (2009)), the results are informative for current policy, and suggest that these type of policies can affect innovation not only by financin the innovative activity of companies that are venture funded, but also by facilitating the diffusion of ideas in the economy.

2.2.5 Back-of-the-envelope calculation

Subject to caveats regarding the representativeness of the IV results discussed in Section 2.2.4 (i.e., LATE vs ATE), a back-of-the-envelope calculation based on the finding is that 1.6% to 10.24% of extra patent production can be attributed to VCs facilitating the diffusion of their targets' patented knowledge. The calculation is as follows. Average annual citations to patents pre-financin are 0.64. VC financin increases annual citations by roughly 20% (using the basic Poisson estimate). Assuming a patent life of 20 years, this implies that each VC-backed patent receives 2.6 extra citations because of increased diffusion caused by VCs.[37] On average, patents

[37] I approximate the life of a patent with 20 years because for utility patents, protection lasts a maximum of 20 years after the application year (provided that renewal fees are paid). However, note that by law patents that have expired still need to be cited if they consitute relevant prior art.

cite 6.5 other patents as relevant art in their applications. Assuming that every citation contributes with at least an equal share of the new innovation, and since 4% of patents have been assigned to VC-backed companies (see the Appendix), this implies that a range of 1.6% to 10.24% of extra patents in the U.S. can be traced-back to VCs facilitating the diffusion of knowledge.[38] This find ing helps explain why researchers using industry-level data estimate that VCs contribute to 14% of patent production (Kortum and Lerner (2000)) in spite of the small percentage of patents assigned to VC-backed companies. The finding in this chapter suggest that part of this difference can be attributed to knowledge spillovers generated by VCs.

2.3 Disentangling Mechanisms

Having shown that VC financin has a causal effect on patent citations, the second part of this chapter turns to disentangling some of the mechanisms behind this effect.

2.3.1 Knowledge Diffusion and VC portfolios

One potential mechanism through which VC affects patent citations is by increasing awareness of companies' innovations, possibly by certifying patents' value, and thus spurring follow-on innovation by other inventors. A second potential mechanism is that VCs facilitate communication among companies in their portfolio, thereby increasing knowledge fl ws in their networks. For example, VCs often organize summits where managers of their companies informally interact. Also, by actively participating in their company boards, VCs can detect technological complementarities across companies in their portfolio, and encourage their portfolio companies to communicate.

To test these two mechanisms, I distinguish between two types of citations:

[38]The calculation of the bounds is as follows: 4%*2.6=10.24% and 10.24%/6.5=1.6%.

1. Portfolio-linked: those from inventors in other companies finance by the same VC.

2. Non-portfolio-linked: Otherwise.

Table 2.10 shows that average annual portfolio-linked citations to patents are 0.002 before VC financing and increase by 305% after VC financing In contrast, annual non-portfolio-linked citations are 0.64 before VC financing and increase by 62% afterwards.[39] To control for changes in citation behavior and in the industry composition of companies over time, I use a similar approach as discussed in Section 2.1.1 and calculate a citation baseline by type of citation. Comparable patents have no portfolio-linked citations because they are not invented by VC-backed companies. In order to classify their citations as portfolio-linked, thus, I use information on the VC-backed company that file the patent in the sample. Table 2.10 shows that after controlling for the aggregate increase in citations using the portfolio-linked (non-portfolio-linked) citation baseline, the percentage increase post VC financin in portfolio-linked (non portfolio-linked) citations decreases from 305% (62%) to 47% (33%).

To formally test these mechanisms, I estimate Poisson models where VC financin is allowed to affect differently each type of citation. I start by estimating the following equation,

$$Cites_{pCt} = \exp\left(\alpha_{pC} + \ln\left(b_{Ct}\right) + \gamma_C D_C + \beta_C D_C \times VC_{pt}\right) \varepsilon_{pCt}, \tag{12}$$

where $Cites_{pCt}$ are citations to patent p, of type C, at time t, where $C \in \{NP, P\}$. NP and P stand for non-portfolio-linked and portfolio-linked, respectively. D_C is a dummy that indicates each type of citation and b_{Ct} corresponds to the citation baseline specifi to the type of citation C. By including b_{Ct} in the estimation, I control for aggregate changes in citations at the technology-class, vintage-

[39]The difference in magnitudes between portfolio- and non portfolio-linked citations reflect the small size of VC portfolios.On average, the companies in my sample join portfolios with 17 other VC-backed companies.

year and type of citation level.[40] VC_{pt} is a dummy that equals one after the issuing company is finance by a VC and ε_{pCt} is an *i.i.d* random variable (with mean equal to 1) that captures idiosyncratic multiplicative shocks at the patent-type of citation level. I include in the estimation patent-cross-type-of-citation fi ed effects, α_{pC}, to control for the time invariant propensity of each patent to received citations of type C. Finally, to test whether the effect of VC financin on citations to patents is stronger inside VC portfolios I test whether β_P and β_{NP} are different. Panel A of Table 2.11 summarizes results. Panel B tests whether the β_Cs are statistically different, using a chi-squared test.

Column 1 of Table 2.11 reports results from estimating equation (12) using a pooled Poisson model that excludes the citation baseline. Standard errors at clustered at the patent level. The interpretation of the coefficien for $D_{NP} \times VC_{pt}$ $(D_P \times VC_{pt})$ is that non-portfolio-linked citations to patents increase by 62.0% (305.2%) after VC financing[41] Panel B confirm that the difference between the estimated coefficient for $D_P \times VC_{pt}$ and $D_{NP} \times VC_{pt}$ is significantl different from zero. Column 2 of Table 2.11 reports results from estimating (12) using a pooled Poisson model. As expected, after controlling for aggregate trends the estimated effect decreases compared to Column 1. Column 3 in Table 2.11 summarizes results from estimating equation (12) including patent-cross-type of citation fi ed effects, which control for unobserved heterogeneity in patents and type of citations. The interpretation of the coefficien for $D_{NP} \times VC_{pt}$ $(D_P \times VC_{pt})$ is that after VC financin non-portfolio-linked (portfolio-linked) citations to a given patent increase by 21.5% (178.5%), relative to the citation baseline. Finally, Panel B confirm that the estimated percentage increase in portfolio-linked citations is statistically larger than in non-portfolio-linked citations.

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[40]This technique is similar to including type of citation cross time fi ed-effects, since it removes any aggregate annual variation by type of citation.

[41]The coefficient of 0.635 and 0.002 for D_{NP} and D_P respectively, represent average portfolio- and non portfolio-linked citations to patents before the VC investment. Note the correspondence of these numbers with the annual averages reported in Table 2.10.

Similar to Section 2.2, in Table 2.12 I address the concern of non-random timing of VC selection using an IV approach. The firs four columns report coefficien estimates using portfolio-linked citations as the dependent variable and instrumenting the timing of VC financin using $Pension_{t-1}$. Although the variation of the instrument is at the state level, the standard errors are clustered at the patent level, because of potential small-cluster bias. The firs four columns show that the effect of VC financin on portfolio-linked citations reported in Table 2.11 remains positive, but is no longer significant This lack of significanc is likely driven by the small number of observations used in these regressions. The last four columns of Table 2.12, report coefficien estimates using non-portfolio-linked citations as the dependent variable. The positive impact of VC financin on non-portfolio-linked citations is robust to controlling for non-random selection by VCs. In addition, the percentage increase in citations is still estimated to be larger for portfolio-linked- citations than for non-portfolio-linked citations, but the difference is no longer significant

In summary, consistent with VC financin increasing awareness of companies' innovations, possibly certifying their value, and spurring follow-on innovation by other inventors, I fin a causal and strong increase in non-portfolio-linked citations. Consistent with VCs facilitating communication across companies in their portfolios, I fin that the increase in portfolio-linked citations is four times stronger than the increase in non-portfolio-linked citations.

Robustness checks and extensions Non-portfolio-linked citations may increase after VC financ ing without an increase in the general awareness of the innovations. For example, the increase in citations may be exclusively concentrated among companies in the VC industry. To test this alternative hypothesis I exclude from the analysis citations from inventors in VC-backed companies. The estimated effect of VC financin is still larger than one and statistically significant consistent with the more general certificatio effect of VC financing

It has been suggested that syndication networks among VC firm matter for performance (Hochberg et al. (2007)). One natural question is whether they also matter for knowledge diffusion. In unreported results, I classify non-portfolio-linked citations as Syndication-linked if the citing company is backed by at least one VC with whom one of the investors of the cited company has syndicated an investment in the past. Using the fi ed effects Poisson model, I estimate the change in Syndication-linked citations after VC-financing There is no clear pattern in the estimated effects across the different specifications

2.3.2 Knowledge Diffusion and Inventor Mobility

Inventors may choose to move to other companies after VC financing For example, if the presence of VC investors implies a transition from creative freedom to a commercial focus (e.g., Aghion et al. (2008)) or if the decision making becomes more centralized with VC arrival (e.g., Seru, 2012). This inventor mobility can facilitate knowledge fl ws between inventors' new and old employers (e.g., Almeida and Kogut (1999), Kim and Marschke (2005), Agrawal and Singh (2011), Azoulay et al. (2012)).

To test this mechanism, I analyze inventor mobility around the VC financin event. This analysis is facilitated by the HBS data-set that includes a unique identifie for inventors after a detailed clean-up and analysis of the original patent records (Lai, D' Amour and Fleming, 2008). Using this identifie , I am able to trace individual mobility in my sample using changes in assignees through time. Overall, I have information on 11,627 inventors that work at VC-backed companies with patents, and their subsequent inventions in the same company or in other assignees. I distinguish between two types of citations:

1. Inventor-linked: citations from inventors who assigned a patent to the VC-backed company before VC-financin
2. Non-inventor-linked: Otherwise

Table 2.13 shows that even after excluding inventor-linked citations from the sample, both portfolio and non-portfolio-linked citations significantl increase after VC financing This type of comparison is informative but is likely to be biased. One concern is that the propensity of inventors to change jobs is not constant over time. To address this concern and also control for aggregate trends in citations and patent life-cycle effects, I follow a similar approach to the one in 2.1.1 construct a citation baseline based on average inventor-linked and non-inventor-linked citations to comparable patents. Column 6 shows that even after controlling for aggregate trends in inventor mobility and citations, the percentage increase in non-inventor-linked citations after VC financin is positive and significant In Tables 2.14 and 2.15, I replicate the Poisson analysis from Section 2.2.2. using non-inventor-linked citations as the dependent variable. As expected from Table 2.13, the results continue to hold. This is evidence that the bulk of the increase in citations post VC financin cannot be linked to inventor mobility.

Note that one drawback from measuring mobility using data on patent assignments is that not all moves are observable. First, I only record movements of inventors; other workers can move and disseminate knowledge. Second, even if I focus on inventor mobility, the data are still necessarily incomplete. I can identify the movement of an inventor only if the individual invents in the new workplace. Some inventors may change jobs and enter executive positions in which they no longer apply for patents, but still influenc the company's innovation. The finding imply, thus, that the effect of VC financin on citations is not fully explained by inventor mobility that is *observable* in the data.

2.3.3 Knowledge Diffusion and Patent Sales

Companies may sell patent outside their core areas after VC financin and directly transfer knowledge to buyers.[42] Prior research has shown an association between VC financin and patent

[42] Also note that patent sales can also be used by VCs to recoup their capital in case of a liquidation.

trade. Katila and Shane (2005) fin that patents are more likely to be licensed in industries where VC financin is prevalent.

To test this mechanism, I collect from the USPTO data on patent reassignments, which acknowledge the transfer of the rights, title, and interest in a patent. A typical assignment is characterized by a unique identifie , the patent number, the names of the buyer (i.e., assignee) and the seller, and the date in which the private agreement between the two parties was signed. After standardizing assignee names, I exclude all records for which the buyer matches the primary assignee of the patent. I also exclude records of administrative events such as a name change.

I combine the clean reassignment data to my sample using patent numbers. Panel A in Table 2.16 reports summary statistics. Of the 2,336 patents in the sample, 375 are sold by their primary assignees. The small number of matches reflect the size of the patent market, only 13.5% of granted patents in the U.S. are ever sold during their life-cycle (Serrano (2010)). Panel B shows that there is an increase in the probability that a patent is sold after VC financing The result holds even after controlling for the likelihood that similar patents are sold. Figure 2.2 illustrates the sharp increase in the probability of a patent sale (solid line), relative to average sales (dashed line), after VC financing

To test whether patent sales explain the effect of VC financin on citations, I split the sample of patents into two groups: those that are sold and those that are not sold by 2012. Panel C of Table 2.16 shows that citations increase post financin for both groups of patents. Thus, although there is an increase in the likelihood that patents are traded after companies are VC financed the subsequent increase in citations cannot be traced to this effect.

One drawback from the reassignment data is that it is not exhaustive of all forms in which a company's IP can be traded (e.g., licenses). My f ndings thus imply that the effect of VC financin on citations is not fully explained by patent trade that is *observable* in the data.

2.3.4 Discussion

Overall, this section points to two mechanisms. First, VC financin increases awareness of innovations, possibly certifie their value, and spurs follow-on innovation by other inventors. There is a causal increase in citations from inventors outside VC portfolios, which cannot be entirely traced back to inventor mobility or to patent sales. This increase in the general awareness of innovations can take several forms. VC financin may act as a certificatio of the quality of innovations or provide the necessary resources for companies to bring their products to market and increase their exposure. Disentangling between these channels is outside the scope of this chapter. As suggestive evidence of increased awareness of companies after VC financing I took the names of companies finance by VCs in 2006 as reported in VentureXpert and downloaded from Google Insights normalized[43] weekly hits for these names in Google from 2004 until 2011.[44] I standardized names by stripping them of punctuation, capitalization, and common acronyms. Consistent with increased exposure post VC financing Figure 3 shows an increase in the number of hits after 2006 for the names of the portfolio companies (solid line) relative to the word "Gold" (dashed-line).

Second, VCs facilitate communication among companies in their portfolios. This effect cannot be entirely traced back to inventor turnover among companies finance by the same VC. One potential channel behind this finding is that VCs encourage their companies to participate in research alliances (Lindsey (2008)), which are known to promote knowledge fl ws (Gomes-Casseres et al. (2006)). Another possibility is that VCs recycle executives across the companies in their portfolio, and knowledge is diffused with top management. Disentangling between these channels is outside the scope of this chapter.

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[43] Weekly searches are divided by the maximum number of searches in the entire period and multiplied by 100.

[44] Data on Google Insights is only available starting on 2004.

2.4 Knowledge Diffusion and Patent Citations

While the analysis so far suggests a strong relationship between VC financin and patent citations, one concern remains. The increase in citations may be due to of a shift in the propensity to cite patents issued by VC-backed companies that is not associated with knowledge fl ws. For example, patent reviewers may also become aware of a company after it is VC financed Since citations from patent reviewers are included in the analysis, citations may increase when there is no diffusion of knowledge. I test this alternative story using the sub-sample of patents file on 2001 for which I can distinguish the citations added by patent reviewers and exclude those from the analysis. Unreported results remain qualitatively similar (although power is significantl reduced).

Another nuanced view is that potential targets may strategically cite patents issued by VC-backed companies in order to attract VC finance To address this concern, I use investments by VCs in public companies as an informal test. Since companies that are public are subject to close monitoring and information disclosures, one should expect no extra boost on diffusion from VC financing unless citations are used strategically by potential targets. In unreported results, I fin that the coefficien estimate of VC_{pt} is close to one and is not statistically significant

A fina alternative story is that the increase in citations is due to "litigation fear." Inventors may decide to cite the patents of a company only after the company is VC financed because the threat of litigation before VC financin is weak. This concern is however minimized to the extent that citations represent no protection against patent infringement law suits.[45] In other words, inventors may choose not to infringe patents once the inventing companies are VC financed but the VC financin event should have little effect on their citation behavior.

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[45]For more on this topic see the Supreme Court Ruling of Microsoft Corp. versus I4I Limited Partnership.

2.5 Conclusion

This chapter investigates how the diffusion of an idea is affected by VC financin of the company that patented the idea. I fin a strong and causal effect on diffusion as measured by patent citations. The empirical evidence points to two mechanisms. First, VCs increase awareness of innovations, possibly by certifying their value to the general public, and influenc the direction of aggregate innovative activity. Second, VCs provide a platform for interaction that facilitates communication across portfolio companies.

The main identificatio challenge in estimating the effect of VC financin on the diffusion of existing knowledge is the endogeneity of VC investments. I address this challenge using time series variation in the size of public pension assets as an instrumental variable. The validity of this approach relies on the home-bias of state pension funds in their VC investments (Hochberg and Rauh (2012)), and on the exclusion restriction that changes in pension assets are independent of companies' innovation opportunities. To address concerns that unobserved economic activity affects both the size of state pension assets and companies' innovation opportunities, I compare citations to patents file by VC-backed companies to those of comparable patents. The exclusion restriction is satisfied thus, as long as the effect of unobserved economic activity on innovation opportunities within a state is uniform across local patents in the same technology-class and vintage-year.

This chapter contributes to our understanding of how financia intermediaries affect innovation. I fin evidence that VCs have a multiplier effect on innovation that goes above and beyond financ ing the innovation of their targets. This result is informative for policy makers that seek to spur innovation by stimulating VC activity. My finding suggest that VC financin increases diffusion of ideas both inside and outside the VC industry, which implies that venture funding not only rewards VC-backed companies, but also creates benefit that are shared by society at large and can have important distributional consequences. However, this feedback from financ to the creation of scientifi knowledge does not necessarily imply that all innovation should be finance through

VCs. By focusing exclusively on research with high short-term rewards more basic research may be sacrificed which can be costly for innovation in the long-run. Assessing the general equilibrium effects of the role of VCs on innovation is a fruitful avenue for future research.

Finally, my findin that VC portfolios are conduits for information fl ws also deserves more attention. I show that the stronger increase in citations inside VC portfolios cannot be explained by inventor turnover among companies that share a common VC. However, it is possible that the mobility of other personnel can explain this concentration of knowledge fl ws inside VC portfolios. There is plenty of informal evidence that VCs recycle executives across portfolio companies. Exploring whether this evidence is systematic, and whether it is associated with knowledge spillovers, are other avenues for future research.

3 Direction of Inventive Activity in Venture Capital Networks

A central characteristic of the Venture Capital (VC) industry is its network-based structure. In contrast to more traditional financia intermediaries, VC investors facilitate relationships among the companies they finance For example, VC investors establish links inside their portfolios by participating in their companies' boards. In addition, VCs tend to syndicate their investments rather than invest alone (Lerner (1994)). Syndicated investments further web VC-backed companies into networks of complex relationships with each other.

While the literature has shown that the links among VC-backed companies matter for performance (e.g., Lindsey (2008), Hochberg et. al (2007)), their effect on the strategic behavior of companies remains understudied. In this chapter, I seek to partially fil this gap by examining how the links among VC-backed companies affect the direction of companies' innovative activity. Theoretically, this effect is not clear. Whereas the presence of common investors can stir companies' research in the same direction by facilitating knowledge spillovers, competition for VCs' financia resources may undermine the incentives of companies to collaborate, or even work in similar areas.

To examine this question empirically, I use patent citations to measure the similarity or convergence between the innovative activity of filin companies. The empirical strategy uses data on patents file by VC-backed companies in the US, and estimates the likelihood of a citation between random pairs of patents. The main explanatory variables are measures of "VC-proximity" as determined by whether the companies that file the patents share a common VC investor, and thus have a "portfolio-link" (e.g., Microsoft and Sun in Figure 3.1), or whether their VC investors are syndication partners and have thus a "syndication-link" (e.g., Microsoft and Resonate in Figure 3.1). My firs findin is that VC proximity increases the likelihood of a citation between patents.

One interpretation of the firs findin is that VC proximity induces companies to pursue similar innovations, for instance, by facilitating the transfer of tacit knowledge among companies. An alternative interpretation is that VCs fund companies that fi well in a strategic sense with the rest of the portfolio, and that the estimated effect reflect this strategic selection. In an attempt to disentangle between these two interpretations, I do two things. First, I control in the regression models for geographical- and technological- proximity among filin companies that can affect both the likelihood of a citation, and their VC-proximity.

Second, since these controls cannot address selection on companies' unobservables, I exploit "indirect" linkages across VC-backed companies.[46] Indirect linkages occur when companies end up connected inside the VC network not because they are finance by the same VC or because their VCs syndicate together, but because their VCs have a common syndication partner (e.g., companies Microsoft and PortalPlayer in Figure 3.1). If indirect linkages occur due to factors that are unrelated to companies' potential fit the estimated impact of indirect links on the likelihood of a citation provides an unbiased instrumental variable estimate of the impact of VC-proximity on the convergence in the innovative activity of companies. As with any exclusion restriction, this assumption cannot be tested. However, it is likely to be satisf ed, as prior research shows that syndication allows VC investors to explore distinct industries and geographies, and invest in companies with lower ex-ante synergy potential with incumbent companies in VC networks (e.g., Kogut et al. (2007), Hochberg et al. (2011)). I fin that VC-proximity as measured by either, portfolio-, syndication- or indirect-linkages, increases the likelihood of a citation between patents, even after controlling for observable similarities between filin companies. Also, the estimated effect of VC-proximity is statistically the same when measured by portfolio-, syndication-, or indirect- linkages. This last result suggests that the VC-proximity effect may not be entirely driven by selection.

Next, I delve deeper into the relation between competition for financia resources and the convergence of innovative activity among VC-backed companies. While it is true that companies that share a common VC are in competition for the firm s financia resources, such competition is, how-

[46]This methodology is similar to Khwaja et al. (2011)

ever, likely to be stronger between pairs of companies in the same technological areas or that are in the same geography. To test whether the competition effect is muffle in the basic estimations, I explore the relation between the interaction of VC-proximity with technological- and geographical-proximity, and the citation likelihood. Interestingly, I fin that portfolio- and syndication-links increase the citation likelihood between patents whose filin companies are technologically dissimilar and geographically distant. In contrast, for patents whose filin companies are technologically or geographically close, sharing a portfolio- or a syndication-link decreases the probability of a citation. In other words, portfolio- and syndication-linkages appear to be substitutes for technological and geographical-proximity.

Finally, I examine potential mechanisms through which VC-proximity affects the likelihood of citations. My finding suggest that the effect is driven by turnover of executives (CEOs, Vice-president etc.) among close VC-backed companies. This result is consistent with Hellmann and Puri (2002), which show that VCs help companies hire personnel for executive positions. These results are also consistent with VC-proximity facilitating convergence of innovation between companies that are technologically distant. Executive skills are more easily transferred across companies in different technological fields in contrast to inventor skills which are likely to be technology-specific

Overall, the finding suggest that the optimal behavior of companies who are competing for the same financia resources is to differentiate, and focus on distinct lines of research. VC-proximity deters convergence of innovative activity for similar companies, and induces companies to seek different areas of specialization. This divergence in the direction of innovation is also convenient for VCs, as it reduces their overall technology-specifi risk. In contrast, for companies who are not in direct competition for VCs' financia resources, such as companies that have an indirect-link or such as companies that share a portfolio-link but that work in different technology areas, VC-proximity provides a platform of interaction that facilitates the diffusion of tacit knowledge and generates interdisciplinary knowledge spillovers. For non competing companies, VC-proximity acts as a bridge for knowledge diffusion, and pushes companies towards working in similar or complementary lines of research.

The contribution to the literature is three-fold. First, this chapter contributes to the literature on competition and innovation. I show that the competition for financia resources affects innovative activity. In contrast, most of the existing studies in this area focus on the impact of product market competition on innovation (e.g., Aghion et al. (2001), Aghion et al. (2005), Dixit and Stiglitz (1977)).

Second, this chapter also relates to the literature on intercompany governance and innovation (e.g., Seru (2007), Schoar (2002), Belenzon and Berkovitz (2010), Belenzon et al. (2010)). While most of this literature has focused on the interaction among companies within conglomerates and business groups, I show that the interaction among companies within VC portfolios also affects innovation.

Finally, this chapter is also related to the literature on the non financia effects of VCs on their investments. Prior research has shown that VCs add value to their companies by helping them fin and hire adequate personnel in their own networks (Hellmann and Puri (2002)). I fin that this executive turnover inside VC networks is a mechanism for knowledge diffusion. More broadly, this findin is also consistent with other papers in the innovation literature that fin evidence of knowledge diffusion across companies through worker turnover (e.g., Kim and Marschke (2005), Agrawal and Singh (2011) and Stoyanov and Zubanov (2012)).

The rest of this chapter is organized as follows. Section 3.1 describes the data. Section 3.2 explains the empirical approach and presents results. Section 3.3 concludes.

3.1 Data

I consider patents file by VC-backed companies between 1976 and 1998, and collect data on all citations received by these patents during a 10-year window since their application year.[47] Because the interest is in the convergence of innovative activity among VC-backed companies, both within-company citations and citations from assignees that are not VC-backed are excluded from the sample.

In order to estimate the likelihood of a citation between random pairs of patents file by VC-backed companies in the US, ideally, one would complement the sample of realized citations with a comprehensive list of all feasible citation dyads among patents file by VC-backed companies. However, using a comprehensive sample poses a practical problem. To illustrate consider the following simple calculation. The number of patents fi ed by VC-backed companies in 2002 was 10,583. The total number of possible citations made by these patents to all other patents file by VC-backed companies is 862,863,739. Using a sample of that size would be computationally too taxing. In addition, it is also not practical. To see why, note that in reality only 11,519 of the 862,863,739 potential citations actually materialized, implying that a citation is a rare event in my setting. An estimation methodology that addresses this characteristic of the dependent variable reduces the variance of maximum-likelihood estimators (Greene (2003)).

Following this intuition, in this chapter I use the approach of Singh and Marx (2013), and implement choice-based sampling to construct a control sample of potential (but unrealized) citations. The choice-based sampling method consists of taking a fraction of the dyads with unrealized citations that is much smaller to the fraction taken of the dyads with realized citations, but that matches the former sample on a number of characteristics. For estimation, I use the weighted-exogenous-sampling maximum-likelihood (WESML) estimator of Manski and Lerman (1977). In order for

[47] A detailed explanation of the construction of the sample of patents file by VC-backed companies can be found in the Appendix.

the choice-based sample to simulate a random exogenous sample, the weight of each observation corresponds to the number of elements it represents from the overall population.

In detail, I start the sampling by matching each citing patent of the realized citations to a random control patent with the same three-digit technology-class and application-year. I make sure the control citing patent is file by a VC-backed company that is different from the company that file the cited patent. I then extend the sample to ensure representation of potentially citing patents belonging to years and/or technology-classes not represented in the original patent citations (and hence in the resulting matched sample). For every cited patent I include an additional observation corresponding to each potential citing year by randomly selecting one potentially citing patent for each year after the application year, and belonging to one of the technology-classes from which no actual citations were received by the cited patent (in that year).

The above steps lead to the fina sample of 344,573 patent pairs, which includes 102,098 actual citations, 102,098 matched pairs and 143,791 additional pairs from citing classes and years not represented in the matched sample. The appropriate weight for each observation is computed using the implied sampling rates for random draws from the relevant subpopulations. The following example illustrates the procedure.

3.1.1 Example of weights

One of the cited patents in my sample is patent 5968136. This patent is classifie under the primary technology-class 713, and was file by Sun Microsystems on 1997. Patent 5968136 was cited by patent 7356705, which Imprivata file on 2002 and was also classifie under the primary technology-class 713. Patent pair (5968136, 7356705), is an observation in the dataset with a weight of one. To construct a matched control pair observation, citing patent 7356705 was matched to control patent 7043649 file by PortalPlayer in 2002 and classifie under technology-class 713. In order to calculate the weight for this observation I construct the size of the actual pool of patents from which patent 7043649 was randomly selected. The calculation is as follows: in year 2002 there were a total of 156 patents classifie in technology-class 713, from which I excluded 25 patents file by Sun Microsystems and patent 7356705. Hence, the number of patents from which patent 7043694 was chosen at random is 130. Patent pair (5968136, 7043649) is therefore included as control pair observation in the dataset with a weight of 130.

Finally, for each of the years between 1997 and 2007, I select a random potentially citing patent file by a company that is not Sun Microsystems and constrained not to be from technology-class 713 for the year 2002. For example, for year 2002 I pick patent 6903052 classifie under technology-class 504 and file by Divergence. The total number of patents file by VC-backed companies in 2002 that were not issued in technology-class 713 is 10,427. The total number of patents applied for in 2002 by Sun that were not issued in technology-class 713 are 957. Hence, the observation (5968136, 6903052) is included in the sample with a weight of 9,470. The range of weights for these 11 observations are between 640 and 9,682, depending on the number of eligible patents in the citing year being considered.

3.1.2 Sample Composition

Table 3.1 shows the composition of the fina sample both in terms of patents and companies. Panel A breaks down the sample by application year of the cited and citing patents. The distribution of application year for the cited patents reflect the construction of the sample. Panel A also breaks down the sample by year in which the companies that file the cited and citing patents were firs finance by a VC. The distribution of these dates follows the investment cycles in the VC industry.

Panel B breaks down the sample by state of the cited and the citing patents. As expected given the importance of Silicon Valley, the state with the largest fraction of cited and citing patents is California. California is followed by Texas, Massachusetts and Washington.

Finally, Panel C breaks the sample down by technology-classes using the 1-digit technology classificatio of Hall et al. (2001). The most common technology-class of the cited patents is Computers and Communications. This technology-class is followed by Drugs and Medical, Electrical and Electronic, Chemical, Mechanical and Others.

3.2 Empirical Approach

I estimate the likelihood of a citation between random pairs of patents using a logit model. As explanatory variables I consider three measures of proximity between pairs of companies: VC, technological and geographical. This section explains in detail the construction of these measures.

3.2.1 VC-proximity

The VC-proximity between two companies is define as the minimum number of intermediate VCs between them. This is analogous to measuring degrees of separation and is a common metric used in network theory. For instance, If two companies share a common VC their VC distance is 0. I assume that an observed syndication marks the beginning of a tie between the VC firms which persists beyond the recorded syndication date. This assumption is also used by other papers that study the syndication network of VCs (Sorenson and Stuart (2001) and Hochberg et al. (2007)). In inferring network ties that exist as of any year t (t being between 1976 and 2008), I include all VCs that invest in VC-backed companies that patent, and their investments in these companies between 1976 and t (including those VCs and companies not associated with the VC-backed companies used for analyzing knowledge fl ws in this chapter).

I consider three types of links between companies based on their VC proximity. Two companies are define to have a portfolio-link at t if their VC distance is 0. Similarly, if two companies have a VC distance of 1, that is, they do not share a common VC, but their two VCs have syndicated a common investment, the pair of companies is define to have a syndication-link at t. Finally, two companies are define to have an indirect-link at t if their VC distance is 2, that is, they do not share a common VC, their VCs have not syndicated an investment in the past, but their VCs share a common VC syndication partner.

The example illustrated in Figure 1 helps clarify these definitions Microsoft Corporation was VC-backed in 1981 by Technology Venture Investors. Later, in 1982, Technology Venture Investors invested in Sun Microsystems. In the data base, thus, Microsoft and Sun have a portfolio-link starting in 1982.

Technology Venture Investors was not the only VC fir to invest in Sun. In total, f ve different VCs invested in Sun Microsystems before it went public, including Kleiner, Perkins, Caufiel and Byers from 1982 to 1984. The company PortalPlayer received money from three different VC investors, none of which invested in Sun, hence, PortalPlayer and Sun do not have a portfolio-link. One of the investors in PortalPlayer was Flatiron Partners in 2000. Flatiron Partners and Kleiner, Perkins, Caufiel and Byers syndicated and investment in Resonate Inc. during 1997. Hence, since Flatiron Partners, the investor in PortalPlayer, and Kleiner, Perkins, Caufiel and Byers, the investor in Sun, share a syndicated investment, in the data, Sun and PortalPlayer have a syndication-link starting in 2000.

Finally, because Microsoft and PortalPlayer do not share a common VC, and their VCs didn't syndicate any investment they have no portfolio- or syndication-link. However, since their VCs have a common syndication partner, in the database they have an indirect-link starting in 2000.

3.2.2 Technological-Proximity

The position of a company in technology space is provided by its share of patents in each USPTO technology-class These shares defin a vector of technological position $T_{it} = (t_{i1t}, ..., t_{iKt})$ for each company i, where t_{ikt} corresponds to the number of patents file by company i in technology-class k until year t. Following Jaffe (1986), the technological-proximity between the pair of companies i and j at year t is calculated as the uncentered correlation between the companies' respective vectors of technological position:

$$Tech\_prox_{ijt} = \frac{\sum_{k=1}^{K} t_{ikt} t_{jkt}}{\sqrt{\sum_{k=1}^{K} t_{ikt}^2 \sum_{k=1}^{K} t_{jkt}^2}}.$$

The technological-proximity measure, *Tech_prox*, ranges between zero and one depending on the degree of technological overlap of the research output between companies.

An example can clarify the construction of this measure of technological-proximity. Sun Microsystems file 5,592 patents between 1982 and 2002 across 99 different 3-digit technology-classes. The squared sum of Sun's patents equals 1,532,256. On the other hand, PortalPlayer file 9 patents between 2001 and 2002 across 8 different technology-classes. The squared sum of PortalPlayer's patents equals 11. For all the technology-classes in which PortalPlayer file patents, Sun had file patents as well. The distribution of patent production across common technology-classes is shown in the table below.

Technology-class	t_{Sunkt}	$t_{PortalPlayerkt}$	$t_{Sunkt} t_{PortalPlayerkt}$
341	16	1	16
369	2	1	2
380	27	1	27
708	146	1	146
710	229	1	229
712	237	1	237
713	180	2	180
718	116	1	116
$\sum_{k=1}^{K} t_{Sunkt} t_{PortalPlayerkt}$			1,133

Given that $\frac{1,133}{\sqrt{1,532,256}*\sqrt{11}} = 0.276$, the technological proximity between Sun and PortalPlayer in 2002 is therefore 0.276.

One drawback of the Jaffe (1986) technological-proximity metric is that it is sensitive to the level of aggregation of technology In particular, the 3-digit technology classificatio used by the USPTO may be too narrowly define to adequately capture the closeness between companies. To address this concern as an alternative measure of closeness I use the 2-digit technology classifica tion suggested by Hall et al. (2001).

3.2.3 Geographical Distance

The calculation of the geographical distance relies upon the HBS dataset. The data by Lai et al. (2009) include inventors' city, state and country of residence. In addition, the authors mapped cities where inventors live to latitudes and longitudes. Using these coordinates, I estimate the geographical distance between two patents using information on the coordinates of the patents' inventors and the Haversine formula to calculate the great-circle distance between two points-that is, the shortest distance over the earth's surface. One natural drawback from this measure of geographical distance is that the city in which inventors live may not coincide with the city in which the work was done. Since the USPTO data has no information on the cities of the assignees this is the best available proxy for an invention's geographical origin.

3.2.4 Summary Statistics

Summary statistics of the key variables used in the analysis are presented in Table 3.2. Of the pairs in the sample, 17.8%, 49.7% and 16.6%, have a portfolio-, syndication- and indirect-link, respectively. For 23% of the pairs, the cited and citing patents have the same 3-digit technology-class. The fraction of pairs for which the cited and citing patents were invented in the same state is 38.9%. The average distance between the cited and citing patents is 2,183 kilometers, and the average technological-proximity is 0.33.

3.2.5 Regression Model

I estimate the likelihood of a citation between random pairs of patents using a logit model. In detail, I estimate the following citation function $\Pr(i, j)$, that specifie the probability that a patent i cites patent j as

$$\Pr(i,j) = \Lambda \left(\begin{array}{c} \alpha' X + \gamma_1 Same\_state + \gamma_2 Same\_class \\ \delta_1 Geo\_dist + \delta_2 Tech\_prox. + \\ \beta_1 Portfolio + \beta_2 Syndication + \beta_3 Indirect \end{array} \right), \tag{13}$$

where $Same\_state$ is a dummy that equals one if both patents have been invented in the same state and $Same\_class$ is a dummy that equals one if both patents are classifie in the same 3-digit technology-class. These dummies control for geographical and technological clustering in patent citations (Hall et. al (2001)). Geo_dist and $Tech\_prox$ correspond to the geographical distance and technological-proximity between the company that invented patent i and the company that invented patent j. $Portfolio$, $Syndication$ and $Indirect$ are all dummies that equal one if the company that invented patent i and the company that invented patent j have a portfolio-, syndication- or indirect-link, respectively.

X is a vector that includes various controls. A full set of indicator variables for the years elapsed between the cited and citing patents in a pair are included to control for citation lag non-parametrically. A separate set of indicator variables for application years of the cited patents are also included. Similarly to Singh (2005) and Singh and Marx (2013), relying upon longitudinal variation, I am able to separately identify cohort effects and citation lag effects in a way that previous studies with more restrictive samples (e.g., Thompson (2006)) were not able to.

To control for the heterogeneity in citation likelihood by technology-class, I include indicators for the cited patent's 3-digit USPTO technology-class. Similarly, to account for the possibility of higher citation rates in certain states, a complete set of dummy variables for the state of the cited patent are included. Also, I include as a control the likelihood of a citation (scaled by 100) between random patents from the population of patents (using data on all patents including those file outside the VC industry) with the same 3-digit primary technology-classes of the cited and citing patents in the pair.

Finally, the probability a patent of a VC-backed company is cited may depend on a variety of characteristics of the VC such as, its skill, the size of its network, and its popularity. To capture these effects in a fl xible way, I introduce a complete set of VC-fir fi ed effects for the lead VC of the company that invented the cited patent. Following Gompers (1996), the lead VC fir is taken to be the one who has invested in the company the longest. Using this definition a lead VC fir cannot be uniquely determined in some cases, for these, I randomly pick one of the VC firm in the syndicate as lead investor.

Estimation I estimate the logit using WESML. Since the sampling is made on the cited patent, I control for common cited patent effects by clustering standard errors at the cited patent level. As a robustness check, I also report standard errors double-clustered at the citing-company and cited-company level, following Cameron et al. (2006). These latter standard errors are reported in squared brackets. Finally, note that the interpretation of the WESML regression estimates is as percentage effects on citation likelihood. To see this note that in a standard logistic model, the marginal effect for a variable i is $\alpha_i\ \Lambda'(.)$ ($\alpha_i\ \Lambda(.) * [1 - \Lambda(.)]$). In general, this expression would need to be calculated either based on the mean predicted probability or using the sample mean for $\Lambda(.)$. However, the fact that citations are rare events allows further simplification since $\Lambda(.)$ is much smaller than 1, $\Lambda(.) * [1 - \Lambda(.)]$ is practically equivalent to $\alpha_i\ \Lambda(.)$ (Singh, 2005). This simplificatio means that the coefficien estimate for α_i can be directly interpreted as the percentage change in citation probability with a unit change in variable i.

3.2.6 Non-Parametric Evidence

Table 3.3 compares the incidence of portfolio-, syndication- and indirect-links in actual citations and control pairs.[48] Panel A shows that the incidence of portfolio and indirect links is statistically greater for actual citations relative to the control pairs. Panel B breaks down the comparison by quartiles of the technological distance between the cited and citing patents. The incidence of portfolio-links is concentrated in those observations where the technological-proximity of the fil ing companies is less than the median. Consistent with the competition for financia resources affecting the direction of innovative activity of companies, the preliminary evidence in this table suggests that portfolio-links and technological-proximity are substitutes in citation likelihood. In constrast, and still consistent with the competition story, the relation between indirect-links and technological-proximity is positive along the distribution of technological-proximity (only negative but insignificantl so, for the third quartile), and is particularly pronounced for the upper quartile of technological-proximity. In other words, unconditionally, indirect-links and technological-proximity are complements.

Panel C breaks down the comparison for state-wide co-located (cited and citing patents invented in the same state) and non-co-located pairs. Similarly to Panel B, Panel C shows that unconditionally, portfolio-links are substitute to collocation in citation likelihood. Again, the result is flippe for syndication-links. Indirect-links are a complement of state collocation.

3.2.7 Estimation Results

VC-proximity positively affects the citation likelihood I begin by verifying the preliminary evidence that the likelihood of a citation is increasing in VC-proximity using a simple version

[48] In this table I only include the firs type of controls where the citing patent is matched to a patent in the same technology-class and with the same application-year.

of the logit model with only the VC-proximity dummies and controls as explanatory variables. Results are presented in column 1 of Table 3.4. The likelihood of a citation between a pair of patents increases by 138.9% if the companies that file the cited and citing patents (cited company and citing company hereafter) have a portfolio-link. This is consistent with the results of Chapter 2. Similarly, the likelihood of a citation also increases if the cited and citing companies share a syndication- or an indirect-link, by 63.5% and 53.1% respectively.

Column 2 in Table 3.4, includes in the logit model relevant control variables such as: an indicator for same three-digit technology-class for both patents in the pair, the citation propensity measure explained above, and a dummy that equals one when the cited and citing patents are invented in the same state. In line with prior studies I fin that knowledge fl ws within the same technology-class and within the same state are stronger than across technology-classes or states. This is indicated by the positive coefficient on the same technology-class and same state dummies. More interestingly, the finding in column 2 imply that the importance of VC-proximity continues to hold even after including the aforementioned controls.

Columns 3 and 4 extend the analysis to include the measures of geographical distance and technological-proximity respectively. Column 3 shows that even after controlling for the geographical distance between the patents, a citation is more likely to occur between patents whose companies have a VC-proximity link. Finally, column 4 shows the importance of controlling for the technological distance between the cited and citing companies in the pair. After controlling for technological-proximity the estimated effects for portfolio-, syndication- and indirect-links, fall considerably, and for the latter two, are no longer signifi ant under double clustering. The coeffi cient of column 4 implies that after controlling for the technological-proximity and geographical distance, a portfolio-link increases the likelihood of a citation by 22%. Finally, note that the positive impact of an indirect-link on the likelihood of a citation continues to hold, which reduces concerns that the results are entirely driven by selection.

Portfolio-links and syndication-links are a substitute for technological-proximity Next, I include in the logit model the interactions between the different proximity measures. Results are presented in columns 4 through 6 of Table 3.4. The main objective is to understand whether the VC-proximity links are a complement or a substitute to technological-proximity and geographical distance. With this view, column 5 in Table 3.4 extends the analysis of column 4 by adding the following interaction terms: $Portfolio \times Same\ state$, $Syndication \times Same\ state$ and $Indirect \times Same\ state$. Interestingly, the estimated coefficient for the firs two interaction terms are negative which suggests that close VC-proximity helps diffuse knowledge only for companies that are in different states, and in fact for companies in the same state, close VC-proximity lowers the probability of a citation. In contrast, the estimated interaction effect for indirect-links is not significant Following Greene (2009), I interpret the results for the interaction terms in this non-linear model graphically by calculating the average predicted effect of a 0 to 1 transition for $Same\ state$. The plots are presented in Figure 3.1. The top figur plots the predicted probabilities of a citation for the different types of VC-proximity links using the model in column 4 which has no second order term. The bottom f gure uses the model in column 5 which includes the second order terms of the interactions. We can interpret the "interaction effect" as the distance between the sets of predicted probabilities among the different types of VC-proximity links. Confirmin expectations, we see that in the expanded model, this interaction effect shows up as an increase in the distance between the predictors by both, decreasing the predicted probability for portfolio-links and syndication-links and, dramatically increasing the predicted probability for indirect-links.

Column 6 in Table 3.4 extends the analysis of column 4 by adding the following interaction terms: $Portfolio \times Tech\_prox$, $Syndication \times Tech\_prox$.and $Indirect \times Tech\_prox$. Similarly to the interactions with the same state dummy, the estimated coefficient for the interaction terms with the technological-proximity measure are negative except for $Indirect \times Tech\_prox$., which is economically small and not significant The estimated coefficient suggest that close VC-proximity is a substitute for technological-proximity. In other words, for companies that are technologically similar, sharing a common VC investor or having VC investors that syndicate together reduces the likelihood of a citation.

I examine the interaction terms between VC- and technological-proximity graphically by calculating the average predicted effect of transitions between the 25th, 50th and 75th percentiles of the empirical distribution of technological-proximity. Results are presented in Figure 3.2. Panel A plots the average predicted probabilities for the different types of VC-proximity links using the model in column 4 of Table 3.4 which has no interaction terms. Panel B plots the predicted probabilities for the expanded model of column 6. The top figur in both Panel A and Panel B, presents the transition from the 25th to the 50th percentile of technological-proximity. The bottom figur in both Panel A and Panel B, presents the transition from the 50th to the 75th percentile of technological-proximity. A comparison between the top and bottom figur within each panel, graphically illustrates the substitutability between VC-proximity and technological-proximity. In other words, for companies that share a common VC, if they are technologically similar they are unlikely to cite each other.[49] A comparison between Panel A and Panel B reflect the effect of the interaction. The interaction effect shows up as increasing the gap between the predicted probabilities for the different VC-proximity links, particularly by increasing (decreasing) the predicted probability for portfolio-links when companies are technologically distant (close). For indirect-links the estimated effect is very different. Companies that have an indirect-link are more likely to cite each other independent of their technological-proximity.

Results are not driven by top states I examine specifi subsamples to figur out whether the finding are driven by particular kinds of patents. First, I subset the sample by removing California as Silicon Valley has often been described as an outlier for diffusion (e.g., Almeida and Kogut (1999)) and, given the concentration of the sample in this state. Results are presented in Table 3.5.

[49]The predicted probability curve as a function of technological distance suggests a non linear effect. I address this issue in unreported results where I include a squared term for technological distance and the corresponding interactions. Results for portfolio-links continue to hold. Numerically results for syndication-links and indirect-links are similar, however, they are no longer significant

The importance of portfolio-links, syndication-links and indirect-links are much more pronounced in this subsample. Although the coefficient on the interactions are still numerically negative, they are no longer significant This does not mean however, that the marginal effects of the interactions are not significan (Ai and Norton (2003)). However, a similar graphical analysis as in the last section, not reported to conserve space, reveals that the interaction effect is not as strong in this subsample. To further investigate whether the finding are state-specifi in ways not captured by the state fi ed effects in the regressions, I also carried out analogous analyses for cited patent subsamples excluding other important states such as Massachusetts, Washington and Texas. The finding revealed that the importance of VC-proximity is also present in these subsamples. In conclusion, the finding are not driven by the largest states in terms of their patent production.

Results are not exclusive to top 1-digit technology-classes I also check whether the results are driven by specifi sectors. I exclude the one-digit Hall et al. (2001) technology category Computers and Communications, the leading sector of patent production by VC-backed companies. As Table 3.6 shows results are qualitatively unchanged. I also carried out analyses for cited patent subsamples for all six different one-digit technology categories. Results are qualitatively similar across the different subsamples.

Role of top VC firm As a last robustness check, I test whether results are driven by top VCs. The VC industry is characterized by heterogeneity in performance and persistence of skill (e.g., Sorensen (2008), Kaplan and Schoar (2005)). It is likely that the importance of VC-proximity is only valid for companies whose lead VCs are among the top performers. To investigate this issue, I exclude from the sample all cited patents file by companies whose lead VC is a top VC firm Top VCs are define as those whose investments represent more than 1% of total investments in the sample, and correspond to: New Enterprise Associates Inc., Kleiner Perkins Caufiel Byers, Oak Investment Partners, U.S. Venture Partners, Mayfiel Fund, Accel Partners, Sequoia Capital and Bessemer Venture Partners. Results are presented in Table 3.5. Results are numerically similar, but no longer significant

Turnover of inventors is not associated with the relation between VC-proximity and citation likelihood I consider potential mechanisms behind the VC-proximity effect. I start by testing whether VC-proximity is a proxy for inventor turnover among companies. It is likely that VCs recycle inventors across their companies. To test whether this mechanism can explain the effect of VC-proximity on the likelihood of a citation, for every observation in the sample I explore whether the filin companies share a common inventor. Two companies are said to share a common inventor at t if there is at least one inventor who assigned patents to both companies at some point before or during year t. The firs two columns of Table 3.8 present results from including in the logit specificatio an indicator for inventor turnover and its interaction with the VC-proximity measures. Column 1 shows that including the indicator for inventor turnover reduces the estimated effect of VC-proximity, however the effect is still positive and significant Unexpectedly, column 2 shows that sharing a common inventor makes it less, instead of more likely for a citation to occur between companies who share a portfolio- or syndication-link. This result may be explained by prior finding that entrepreneurial spawning actually operate in new lines of businesses (Gompers et al. (2005))

Turnover of executives drives the relation between VC proximity and citation likelihood Next I consider turnover of executives. One of the fundamental value-adding roles of VCs is helping them hire (Hellmann and Puri (2002)), and considerable overlap exists among the executives of companies that share a common VC. To test whether turnover of executives is behind the effect of VC-proximity, for every observation in the sample I explore whether the filin companies share a common executive. Two companies are said to share a common executive at t if there is at least one executive who worked on these companies at some point before, or during. year t. The last two columns of Table 3.8 present results from including in the logit specificatio an indicator for executive turnover and its interaction with the VC-proximity measures. Column 3 shows that the indicator for executive turnover is not significan and has no effect on the estimated effects for VC-proximity. However, column 4 shows that after including the interactions, it is clear that the effect of VC-proximity occurs only when companies share common executives. This result is interesting, as it is evidence of a clear mechanism that facilitates knowledge diffusion inside VC networks, namely, executive turnover.

Results from this section are overall consistent with VC-proximity facilitating knowledge diffusion among companies that are technologically distant. Executive skills are likely to be more transferable across companies in different technological areas, whereas inventor skills are likely to be more technology specific

3.3 Conclusions

This chapter investigates the relationship between the strategic interaction among companies inside VC networks and the direction of innovative activity. I fin that companies in the same VC network and in similar technological or geographical areas tend to diverge in the direction of their innovative activity. In contrast, companies in different technologies or geographies, but within the same VC network, tend to converge in the direction of their patented research. The firs findin could derive from the competition for finan ial resources inside VC networks (e.g., Townsend (2012)). The second findin may be associated to VCs facilitating relational contracting (e.g., Lindsey (2008)).

This chapter also has some interesting finding regarding the mobility of workers and knowledge spillovers. I fin that the convergence in innovative activity in VC networks is associated with turnover of executives among VC-backed companies, but not with turnover of inventors. Given the technology-specificit of inventor skill, and the more fl xible nature of executive skills, this findin is consistent with most of the convergence in innovative activity inside VC networks occurring among companies that are technologically dissimilar.

Given the importance of innovation on economic growth, understanding how financia intermediaries can shape the direction of innovative activity is of paramount interest. Most of the existing research focuses on how financ and corporate governance can affect the rate of innovative activity. However, the quantity of innovations produced is not the only issue of interest in welfare economics, but also, how diverse is the production of commodities and innovations. The VC industry provides a particularly good setting for understanding how financ can affect this diversity, hence, there are many directions that future research can take. For instance, although VC-backed companies are often posed as stand-alone innovators in theoretical models (e.g., Belenzon et al. (2010)), conceptually VC firm share many characteristics with conglomerates. For example, decision making is partially centralized as VCs often participate in their companies' boards, and capital fl ws akin to internal capital markets are also likely to be present (e.g.,Townsend (2012)). Understanding how the structure of VC firm resembles conglomerates, and the predictions of those similarities on the interaction among VC-backed companies and the impact on their innovative activity, is an interesting area for future research.

4 Tables

Table 1.1 – Sample Composition

The sample is composed of 36,980 patents invented by 4,169 companies and filed (applied for) during the period between 3 years before and 5 years after the VC investment. Panel A describes the distribution of patent applications and VC investments over time as well as the type of exit by the VC firm. Panel B describes the industry distribution of companies and patents.

Panel A. Distribution of VC investments by year and exit

Year	VC investments	Defunct	Other	Acquisition	Active	IPO	Patent Applications	Patent Grant
1976							23	
1977							38	10
1978							63	27
1979	31	7	1	12	1	10	96	30
1980	53	13	4	20	2	14	105	59
1981	101	23	4	47	8	19	177	81
1982	90	18	8	40	6	18	227	90
1983	90	24	2	40	7	17	273	131
1984	108	31	8	40	5	24	355	212
1985	84	22	2	38	2	20	389	261
1986	74	21	3	35	5	10	443	314
1987	101	36	5	25	7	28	494	444
1988	94	27	2	28	7	30	544	427
1989	126	28	10	47	12	29	518	589
1990	83	18	2	39	4	20	516	556
1991	53	16	3	15	6	13	483	517
1992	70	15	2	24	3	26	548	479
1993	85	11	6	20	10	38	615	478
1994	89	17	7	36	10	19	881	514
1995	164	38	2	58	20	46	1,183	549
1996	202	39	6	72	29	56	1,170	643
1997	232	39	4	106	34	49	1,706	825
1998	273	50	8	100	62	53	2,148	1,245
1999	324	47	12	129	95	41	2,352	1,394
2000	487	73	12	184	176	42	3,145	1,675
2001	300	36	3	102	134	25	3,773	1,953
2002	240	16	3	81	120	20	3,322	2,191
2003	234	11	3	67	140	13	2,217	2,725
2004	221	5	10	64	131	11	1,775	2,719
2005	160	2	1	34	119	4	1,177	2,439
2006							409	3,058
2007							93	2,487
2008							5	2,141
Total	4,169	683	133	1,503	1,155	695	31,263	31,263

Panel B. Industry distribution of companies and patents

	# of companies	# of patents
Biotechnology	428	4,070
Communications and Media	612	4,434
Computer Related	1,272	6,001
Medical Health Life Science	698	6,819
Non-High Technology	469	2,794
Semiconductors Other Elect	690	7,145
	4,169	31,263

Table 1.2 - Univariate tests of rate and quality of innovative activity

This table compares the rate of innovative activity, as measured by patent filings, before and after the VC investment. Panel B compares the quality and nature of innovative activity, as measured by different patent-based metrics explained in detail in Section 2, before and after venture funding. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A

	Patent Production					
	Mean	Std. Dev.	Min	Median	Max	Obs.
Pre VC	0.37	1.28	0	0	38	12,507
Post VC	1.09	2.99	0	0	95	24,473
Difference	0.85***					36,980
Ratio	2.99					

Panel B

	Mean Pre-VC	Obs.	Mean Post-VC	Obs.	Diff.	P- value
Cites	9.192	3,393	9.158	17,745	0.034	0.907
Self-cites	1.179	3,393	1.322	17,745	0.144*	0.090
Non self-cites	8.013	3,393	7.836	17,745	-0.177	0.493
Originality	0.575	2,887	0.571	15,657	-0.004	0.558
Generality	0.839	3,160	0.825	16,338	-0.014***	0.009
Scaled cites	1.875	3,393	1.900	17,745	0.026	0.616
Scaled self-cites	2.105	3,389	2.158	17,743	0.053	0.683
Scaled non self-cites	1.844	3,393	1.833	17,745	-0.011	0.835
Scaled originality	1.121	2,886	1.115	15,657	-0.005	0.667
Scaled generality	1.154	3,160	1.143	16,338	0.011	0.219

Table 1.3 - VC and the rate of innovative activity

The table contains Poisson regression estimates. An observation is a company-year. The dependent variable is successful patent applications. $After\ VC$ is an indicator variable that equals 1 after VC investment. $Interim\ VC$ is a dummy that equals 1 while the company is being financed by at least one VC. $After\ Exit$ is a dummy that equals 1 after all VC investors exit a company. While we don't have information on the exact date that each VC exits its investments, we approximate it as one year after the last observed financing round. The models include company and year fixed effects. The specification labeled “Full Sample” includes all patents. The specification labeled “After 1999” (“Before 1999”) includes only companies involved in VC (initial) investments after (before) 1999. The reported coefficients are incidence rates. A coefficient greater than one corresponds to a positive relationship between the explanatory variable and production intensity. Standard errors are clustered at the issuing company level. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A

	Full Sample	Year VC investment		Companies with patents before and after VC investment
		After 1999	Before 1999	
	(1)	(2)	(3)	(4)
After VC	2.535***	2.268***	2.422***	1.614***
	(0.121)	(0.159)	(0.178)	(0.096)
Observations	36,980	17,153	19,827	9,543
N. Companies	4,169	1,966	2,203	1,081
Year FE	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes

Panel B

	Full Sample	Year VC investment		Companies with patents before and after VC investment
		After 1999	Before 1999	
	(1)	(2)	(3)	(4)
Interim VC (I)	2.167***	1.934***	2.189***	1.482***
	(0.098)	(0.122)	(0.154)	(0.082)
After Exit (II)	1.335***	0.827	1.626***	1.007
	(0.101)	(0.110)	(0.171)	(0.105)
p-value Chi 2 test (I=II)	0.00	0.00	0.00	0.00
Observations	36,980	17,153	19,827	9,543
N. Companies	4,169	1,966	2,203	1,081
Year FE	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes

Table 1.4 - VC and the rate of innovative activity by industry

The table contains Poisson regression estimates. An observation is a company-year. The dependent variable is successful patent applications. $After\ VC$ is an indicator variable that equals 1 after VC investment. $Interim\ VC$ is a dummy that equals 1 while the company is being financed by at least one VC. $After\ Exit$ is a dummy that equals 1 after all VC investors exit a company. While we don't have information on the exact date that each VC exits its investments, we approximate it as one year after the last observed financing round. The models include company and year fixed effects. The specification labeled "Full Sample" includes all patents. The specification labeled "After 1999" ("Before 1999") includes only companies involved in VC (initial) investments after (before) 1999. We use the industry classification as reported by SDC and described in Panel B of Table 1. The reported coefficients are incidence rates. A coefficient greater than one corresponds to a positive relationship between the explanatory variable and production intensity. Standard errors are clustered at the issuing company level. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A

	Full Sample	Year of VC investment	
		After 1999	Before 1999
	(1)	(2)	(3)
After VC × Biotech (II)	3.055***	1.877***	4.485***
	(0.393)	(0.346)	(0.837)
After VC × Comm. Media (III)	2.770***	2.463***	2.603***
	(0.316)	(0.372)	(0.559)
After VC × Computer (IV)	2.273***	1.912***	2.289***
	(0.206)	(0.212)	(0.370)
After VC × Medical Health (V)	(2.395***	1.999***	2.498***
	(0.197)	(0.235)	(0.319)
After VC × Non High Tech (I)	1.673***	2.264***	1.261
	(0.212)	(0.425)	(0.204)
After VC × Semiconductors (VI)	2.967***	2.748***	2.507***
	(0.303)	(0.342)	(0.391)
P-value Chi 2 test			
II=I	0.00	0.47	0.00
III=I	0.00	0.71	0.01
IV=I	0.04	0.42	0.01
V=I	0.02	0.56	0.00
VI=I	0.00	0.40	0.00
Observations	36,980	17,153	19,827
N. companies	4,169	1,966	2,203
Company FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Panel B

	Full Sample	Year of VC investment	
		After 1999	Before 1999
	(1)	(2)	(3)
Interim VC × Biotech (I)	2.261***	1.675***	3.029***
	(0.267)	(0.277)	(0.528)
Interim VC × Comm. Media (II)	2.380***	2.217***	2.147***
	(0.252)	(0.300)	(0.399)
Interim VC × Computer (III)	2.173***	1.776***	2.394***
	(0.171)	(0.174)	(0.332)
Interim VC × Medical Health (IV)	2.098***	1.685***	2.378***
	(0.159)	(0.188)	(0.265)
Interim VC × Non High Tech (V)	1.463***	1.631***	1.324**
	(0.154)	(0.280)	(0.168)
Interim VC × Semiconductors (VI)	2.452***	2.253***	2.186***
	(0.235)	(0.262)	(0.309)
After Exit × Biotech (IA)	2.042***	0.789	3.279***
	(0.342)	(0.297)	(0.658)
After Exit × Comm. Media (IIA)	1.466*	0.942	1.732*
	(0.299)	(0.282)	(0.539)
After Exit × Computer (IIIA)	1.185	0.930	1.409*
	(0.171)	(0.220)	(0.282)
After Exit × Medical Health (IVA)	1.248*	0.747	1.591***
	(0.150)	(0.147)	(0.250)
After Exit × Non High Tech (VA)	0.804	0.857	0.836
	(0.182)	(0.361)	(0.210)
After Exit × Semiconductors (VIA)	1.417**	0.718	1.821***
	(0.214)	(0.148)	(0.390)
P-value Chi 2 test			
I=IA	0.37	0.03	0.50
II=IIA	0.01	0.00	0.34
III=IIIA	0.00	0.00	0.00
IV=IVA	0.00	0.00	0.00
V=VA	0.00	0.08	0.05
VI=VIA	0.00	0.00	0.26
Observations	36,980	17,153	19,827
N. companies	4,169	1,966	2,203
Company FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table 1.5 - VC and the rate of innovative activity by type of VC exit

The table contains Poisson regression estimates. An observation is a company-year. The dependent variable is successful patent applications. $After\ VC$ is an indicator variable that equals 1 after VC investment. $Interim\ VC$ is a dummy that equals 1 while the company is being financed by at least one VC. $After\ Exit$ is a dummy that equals 1 after all VC investors exit a company. While we don't have information on the exact date that each VC exits its investments, we approximate it as one year after the last observed financing round. The models include company and year fixed effects. The specification labeled “Full Sample” includes all patents. The specification labeled “After 1999” (“Before 1999”) includes only companies involved in VC (initial) investments after (before) 1999. We use the type of exit as reported by SDC and described in Panel A of Table 1. The reported coefficients are incidence rates. A coefficient greater than one corresponds to a positive relationship between the explanatory variable and production intensity. Standard errors are clustered at the issuing company level. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A

	Full Sample	Year of VC investment	
		After 1999	Before 1999
	(1)	(2)	(3)
Interim VC × Defunct (I)	1.535***	1.775***	1.372***
	(0.146)	(0.315)	(0.150)
Interim VC × Other (II)	1.527**	1.075	1.958**
	(0.285)	(0.293)	(0.541)
Interim VC × Acquisition (III)	2.155***	1.777***	2.293***
	(0.168)	(0.193)	(0.241)
Interim VC × Active	2.333***	2.108***	2.097***
	(0.154)	(0.167)	(0.287)
Interim VC × Public (IV)	2.523***	1.781***	3.074***
	(0.248)	(0.268)	(0.415)
After Exit × Defunct (IA)	0.349***	0.270***	0.383***
	(0.057)	(0.073)	(0.075)
After Exit × Other (IIA)	1.043	0.925	1.333
	(0.331)	(0.356)	(0.632)
After Exit × Acquisition (IIIA)	0.988	0.617***	1.247
	(0.110)	(0.107)	(0.186)
After Exit × Public (IVA)	2.554***	1.337	3.602***
	(0.320)	(0.275)	(0.596)
P-value Chi 2 test			
I=IA	0.00	0.00	0.00
II=IIA	0.14	0.68	0.21
III=IIIA	0.00	0.00	0.00
IV=IVA	0.86	0.08	0.06
Observations	36,980	17,153	19,827
N. companies	4,169	1,966	2,203
Company FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table 1.6 - VC and the quality of innovative activity

The table contains pooled Poisson regression estimates. An observation is a patent. The dependent variable is reported at the top of each column. *Cites* correspond to the number of times the patent has been cited by other patents in the calendar years of the patent grant and the 3 subsequent years. *Non-self-cites* (*Self-cites*) exclude from (only include in) the citation count those citations made by other patents filed by the same company. $After\ VC$ is an indicator variable that equals 1 after VC investment. $Interim\ VC$ is a dummy that equals 1 while the company is being financed by at least one VC. $After\ Exit$ is a dummy that equals 1 after all VC investors exit a company. While we don't have information on the exact date that each VC exits its investments, we approximate it as one year after the last observed financing round. The reported coefficients are incidence rates. A coefficient greater than one corresponds to a positive relationship between the explanatory variable and the citation intensity. Standard errors are clustered at the issuing company level. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A

	(1)	(2)	(2)	(6)	(7)	(8)
	Cites	Self-cites	Non- self-cites	Cites	Self-cites	Non Self-cites
After VC	0.996	1.122	0.978	1.016	1.101	1.003
	(0.063)	(0.180)	(0.061)	(0.050)	(0.170)	(0.046)
Constant	9.192***	1.179	8.013***	1.859***	2.007***	1.840***
	(0.468)	(0.121)	(0.412)	(0.074)	(0.195)	(0.072)
Observations	21,138	21,138	21,138	21,138	21,132	21,138
N. Companies	3,231	3,231	3,231	3,231	3,231	3,231
Offset b	No	No	No	Yes	Yes	Yes

Panel B

	(1)	(2)	(2)	(6)	(7)	(8)
	Cites	Self-cites	Non- self-cites	Cites	Self-cites	Non Self-cites
Interim VC	1.076	1.226	1.054	1.089*	1.196	1.072
	(0.067)	(0.192)	(0.063)	(0.055)	(0.179)	(0.050)
After Exit	0.871	0.958	0.858*	0.900*	0.950	0.892**
	(0.074)	(0.224)	(0.073)	(0.055)	(0.215)	(0.051)
Constant	9.192***	1.179	8.013***	1.859***	2.007***	1.840***
	(0.468)	(0.121)	1.054	(0.074)	(0.195)	(0.072)
p-value Chi 2 test (I=II)	0.00	0.21	0.00	0.00	0.23	0.00
Observations	21,138	21,138	21,138	21,138	21,132	21,138
N. companies	3,231	3,231	3,231	3,231	3,231	3,231
Offset b	No	No	No	Yes	Yes	Yes

Panel C: Dynamics before the VC exit

	(1)	(2)	(3)	(6)	(7)	(8)
	Cites	Self-cites	Non- self-Cites	Cites	Self-cites	Non Self-cites
Event Year -3	0.836*	1.011	0.813**	0.936	1.092	0.915
	(0.086)	(0.231)	(0.084)	(0.079)	(0.239)	(0.074)
Event Year -2	0.808**	0.880	0.798***	0.893	0.923	0.888
	(0.068)	(0.157)	(0.069)	(0.065)	(0.158)	(0.065)
Event Year -1	0.917	0.978	0.909	0.936	0.988	0.929
	(0.063)	(0.146)	(0.065)	(0.054)	(0.138)	(0.055)
Event Year +1	1.035	1.364*	0.991	1.087	1.375*	1.047
	(0.065)	(0.223)	(0.061)	(0.062)	(0.224)	(0.056)
Event Year +2	0.937	1.315	0.887	1.008	1.297	0.966
	(0.078)	(0.268)	(0.071)	(0.069)	(0.256)	(0.061)
Event Year +3	0.874	1.204	0.830*	0.982	1.221	0.946
	(0.089)	(0.346)	(0.080)	(0.088)	(0.345)	(0.077)
Event Year +4	0.741***	0.891	0.721***	0.924	0.949	0.919
	(0.075)	(0.238)	(0.074)	(0.076)	(0.243)	(0.076)
Event Year +5	0.612***	0.798	0.588***	0.767***	0.869	0.752***
	(0.068)	(0.199)	(0.070)	(0.073)	(0.211)	(0.074)
Constant	10.632***	1.237	9.395***	2.016***	2.032***	2.014***
	(0.582)	(0.173)	(0.518)	(0.099)	(0.271)	(0.098)
Observations	14,655	14,655	14,655	14,655	14,649	14,655
N. companies	2,907	2,907	2,907	2,907	2,906	2,907
Offset b_t	No	No	No	Yes	Yes	Yes

Table 1.7 - VC and the quality of innovative activity by industry

The table contains pooled Poisson regression estimates. An observation is a patent. The dependent variable is reported at the top of each column. *Cites* correspond to the number of times the patent has been cited by other patents in the calendar years of the patent grant and the 3 subsequent years. *Non self-cites* (*Self-cites*) exclude from (only include in) the citation count those citations made by other patents filed by the same company. $After\ VC$ is an indicator variable that equals 1 after VC investment. $Interim\ VC$ is a dummy that equals 1 while the company is being financed by at least one VC. $After\ Exit$ is a dummy that equals 1 after all VC investors exit a company. While we don't have information on the exact date that each VC exits its investments, we approximate it as one year after the last observed financing round. We use the industry classification as reported by SDC and described in Panel B of Table 1. The reported coefficients are incidence rates. A coefficient greater than one corresponds to a positive relationship between the explanatory variable and the citation intensity. Standard errors are clustered at the issuing company level. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Cites	Self-cites	Non- self-cites	Cites	Self-cites	Non- self-cites
$\mathrm{Interim\ VC} \times \mathrm{Biotech}$ (I)	0.691**	1.524	0.573***	1.009	1.603*	0.883
	(0.102)	(0.475)	(0.076)	(0.102)	(0.422)	(0.071)
$\mathrm{Interim\ VC} \times \mathrm{Comm.Media}$ (II)	1.238**	0.563***	1.334***	1.080	0.667*	1.123
	(0.117)	(0.118)	(0.131)	(0.078)	(0.142)	(0.082)
$\mathrm{Interim\ VC} \times \mathrm{Computer}$ (III)	1.463***	1.378	1.475***	1.173	1.309	1.159**
	(0.160)	(0.763)	(0.113)	(0.127)	(0.718)	(0.080)
$\mathrm{Interim\ VC} \times \mathrm{Medical\ Health}$ (IV)	1.309***	1.467**	1.287**	1.109	1.136	1.104
	(0.126)	(0.223)	(0.130)	(0.094)	(0.168)	(0.098)
$\mathrm{Interim\ VC} \times \mathrm{Non\ High\ Tech}$ (V)	0.754*	1.421	0.659***	1.020	1.513	0.925
	(0.129)	(0.512)	(0.100)	(0.133)	(0.464)	(0.111)
$\mathrm{Interim\ VC} \times \mathrm{Semiconductors}$ (VI)	0.850	1.243	0.794**	1.035	1.336	0.985
	(0.091)	(0.295)	(0.079)	(0.103)	(0.307)	(0.090)
$\mathrm{After\ Exit} \times \mathrm{Biotech}$ (IA)	0.512***	1.164	0.419***	0.828	1.376	0.714***
	(0.085)	(0.538)	(0.050)	(0.107)	(0.594)	(0.074)
$\mathrm{After\ Exit} \times \mathrm{Comm.Media}$ (IIA)	0.832	0.213***	0.921	0.751***	0.253***	0.804**
	(0.116)	(0.046)	(0.134)	(0.065)	(0.054)	(0.071)
$\mathrm{After\ Exit} \times \mathrm{Computer}$ (IIIA)	1.222*	0.881	1.271**	0.997	0.766	1.028
	(0.135)	(0.415)	(0.144)	(0.087)	(0.367)	(0.079)
$\mathrm{After\ Exit} \times \mathrm{Medical\ Health}$ (IVA)	1.323*	1.635	1.279*	0.961	1.202	0.927
	(0.195)	(0.740)	(0.180)	(0.108)	(0.530)	(0.088)
$\mathrm{After\ Exit} \times \mathrm{Non\ High\ Tech}$ (VA)	0.537***	1.134	0.453***	0.811	1.300	0.714***
	(0.098)	(0.543)	(0.055)	(0.161)	(0.606)	(0.084)
$\mathrm{After\ Exit} \times \mathrm{Semiconductors}$ (VIA)	0.682***	0.671	0.684***	0.850	0.763	0.863
	(0.088)	(0.206)	(0.097)	(0.103)	(0.246)	(0.112)
Constant	8.996***	1.121	7.875***	1.855***	1.931***	1.845***
	(0.502)	(0.110)	(0.465)	(0.088)	(0.182)	(0.092)
P-value Chi 2 test						
I=IA	0.13	0.60	0.04	0.16	0.75	0.03

II=IIA	0.00	0.00	0.01	0.00	0.00	0.00
III=IIIA	0.11	0.00	0.19	0.08	0.00	0.16
IV=IVA	0.93	0.78	0.96	0.13	0.88	0.04
V=VA	0.01	0.27	0.01	0.10	0.49	0.06
VI=VIA	0.02	0.04	0.14	0.02	0.07	0.12
Observations	21,138	21,138	21,138	21,138	21,132	21,138
N. companies	3,231	3,231	3,231	3,231	3,231	3,231
Offset b	No	No	No	Yes	Yes	Yes

Table 1.8 - VC and the quality of innovative activity by type of VC exit

The table contains pooled Poisson regression estimates. An observation is a patent. The dependent variable is reported at the top of each column. *Cites* correspond to the number of times the patent has been cited by other patents in the calendar years of the patent grant and the 3 subsequent years. *Non self-cites* (*Self-cites*) exclude from (only include in) the citation count those citations made by other patents filed by the same company. $After\ VC$ is an indicator variable that equals 1 after VC investment. $Interim\ VC$ is a dummy that equals 1 while the company is being financed by at least one VC. $After\ Exit$ is a dummy that equals 1 after all VC investors exit a company. While we don't have information on the exact date that each VC exits its investments, we approximate it as one year after the last observed financing round. We use the type of exit as reported by SDC and described in Panel A of Table 1. The reported coefficients are incidence rates. A coefficient greater than one corresponds to a positive relationship between the explanatory variable and the citation intensity. Standard errors are clustered at the issuing company level. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Cites	Self-cites	Non- self-cites	Cites	Self-cites	Non- self-cites
Interim VC × Acquisition (I)	1.130	1.266	1.110	1.110	1.208	1.095
	(0.103)	(0.425)	(0.085)	(0.093)	(0.395)	(0.073)
Interim VC × Active	0.885	1.338*	0.820*	1.096	1.357**	1.047
	(0.098)	(0.215)	(0.099)	(0.104)	(0.211)	(0.109)
Interim VC × Defunct (II)	0.964	0.242***	1.066	0.882*	0.233***	0.969
	(0.089)	(0.037)	(0.102)	(0.062)	(0.036)	(0.071)
Interim VC × Other (III)	0.673**	0.327***	0.723*	0.687***	0.334***	0.738**
	(0.105)	(0.090)	(0.120)	(0.100)	(0.097)	(0.112)
Interim VC × Public (IV)	1.317***	1.924***	1.230**	1.209**	1.813***	1.126
	(0.125)	(0.294)	(0.123)	(0.096)	(0.263)	(0.091)
After Exit × Acquisition (IA)	0.903	0.723	0.929	0.873	0.700	0.897
	(0.124)	(0.246)	(0.129)	(0.076)	(0.234)	(0.072)
After Exit × Defunct (IIA)	0.610***	0.217***	0.666***	0.715***	0.210***	0.803**
	(0.070)	(0.063)	(0.081)	(0.070)	(0.060)	(0.081)
After Exit × Other (IIIA)	0.990	0.201***	1.102	0.791***	0.179***	0.869
	(0.284)	(0.077)	(0.317)	(0.070)	(0.051)	(0.076)
After Exit × Public (IVA)	0.928	1.380	0.864	0.945	1.354	0.884
	(0.103)	(0.399)	(0.095)	(0.079)	(0.375)	(0.067)
Constant	8.996***	1.121	7.875***	1.855***	1.931***	1.845***
	(0.502)	(0.110)	(0.465)	(0.088)	(0.182)	(0.092)
P-value Chi 2 test						
I=IA	0.07	0.01	0.14	0.00	0.00	0.01
II=IIA	0.00	0.70	0.00	0.04	0.71	0.07
III=IIIA	0.22	0.28	0.18	0.34	0.10	0.29
IV=IVA	0.00	0.15	0.00	0.00	0.18	0.00
Observations						
N. companies						
Offset b	No	No	No	Yes	Yes	Yes

Table 1.9 - VC quality of innovative activity with company fixed effects

The table contains Poisson regression estimates that include company fixed-effects. An observation is a patent. The dependent variable is reported at the top of each column. *Cites* correspond to the number of times the patent has been cited by other patents in the calendar years of the patent grant and the 3 subsequent years. *Non self-cites* (*Self-cites*) exclude from (only include in) the citation count those citations made by other patents filed by the same company. $After\ VC$ is an indicator variable that equals 1 after VC investment. $Interim\ VC$ is a dummy that equals 1 while the company is being financed by at least one VC. $After\ Exit$ is a dummy that equals 1 after all VC investors exit a company. While we don't have information on the exact date that each VC exits its investments, we approximate it as one year after the last observed financing round. The reported coefficients are incidence rates. A coefficient greater than one corresponds to a positive relationship between the explanatory variable and the citation intensity. Standard errors are clustered at the issuing company level. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Cites	Self-cites	Non-self-cites	Cites	Self-cites	Non-self-cites	Cites	Non-self-cites
After VC	0.719***	0.387***	0.782***					
	(0.032)	(0.047)	(0.034)					
Interim VC (I)				0.795***	0.466***	0.850***		
				(0.036)	(0.052)	(0.038)		
After Exit (II)				0.565***	0.242***	0.640***		
				(0.036)	(0.040)	(0.041)		
Event Year -3							1.448***	1.272**
							(0.147)	(0.119)
Event Year -2							1.213***	1.150**
							(0.071)	(0.067)
Event Year -1							1.154***	1.116**
							(0.056)	(0.058)
Event Year +1							0.887**	0.906**
							(0.044)	(0.042)
Event Year +2							0.753***	0.777***
							(0.039)	(0.040)
Event Year +3							0.702***	0.750***
							(0.047)	(0.050)
Event Year +4							0.697***	0.757***
							(0.052)	(0.061)
Event Year +5							0.616***	0.691***
							(0.061)	(0.072)
Constant	2.544***	1.602***	2.474***				2.428***	2.455***
	(0.114)	(0.195)	(0.107)				(0.123)	(0.123)
p-value Chi 2 tes (I=II)				0.00	0.00	0.00		
Observations	21,138	21,132	21,138	21,138	21,132	21,138	14,245	14,245
N. Companies	3,231	3,231	3,231	3,231	3,231	3,231	2,867	2,867
Offset b	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 1.10 - VC and the nature of innovative activity

The table contains Poisson regression estimates. An observation is a patent. The dependent variable is reported at the top of each column. *Originality* and *Generality* are patent-based metrics of the novelty of patents and are described in Section 1.2.3. $After\ VC$ is an indicator variable that equals 1 after VC investment. $Interim\ VC$ is a dummy that equals 1 while the company is being financed by at least one VC. $After\ Exit$ is a dummy that equals 1 after all VC investors exit a company. While we don't have information on the exact date that each VC exits its investments, we approximate it as one year after the last observed financing round. The reported coefficients are incidence rates. A coefficient greater than one corresponds to a positive relationship between the explanatory variable and the dependent variable. Standard errors are clustered at the issuing company level. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A

	(1)	(2)	(3)	(4)	(5)	(6)
	Originality	Originality	Originality	Generality	Generality	Generality
After VC	0.994	0.994	0.937***	0.983*	0.995	0.971***
	(0.017)	(0.015)	(0.017)	(0.010)	(0.009)	(0.009)
Constant	0.575***	1.111***	1.334***	0.839***	1.134***	1.366***
	(0.009)	(0.015)	(0.023)	(0.007)	(0.010)	(0.013)
Observations	18,544	18,543	18,543	19,498	19,498	19,498
N. Companies	3,034	3,034	3,034	3,116	3,116	3,116
Offset b	No	Yes	Yes	No	Yes	Yes
Company FE	No	No	Yes	No	No	Yes

Panel B

	(1)	(2)	(3)	(4)	(5)	(6)
	Originality	Originality	Originality	Generality	Generality	Generality
Interim VC	1.005	1.006	0.939***	0.990	1.006	0.978**
	(0.017)	(0.015)	(0.017)	(0.010)	(0.010)	(0.009)
After Exit	0.976	0.975	0.932***	0.972**	0.978**	0.957***
	(0.020)	(0.017)	(0.019)	(0.014)	(0.011)	(0.011)
Constant	0.575***	1.111***	1.331***	0.839***	1.134***	1.355***
	(0.009)	(0.015)	(0.024)	(0.007)	(0.010)	(0.013)
p-value Chi 2 test (I=II)	0.08	0.02	0.61	0.13	0.00	0.00
Observations	18,544	18,543	18,543	19,498	19,498	19,498
N. Companies	3,034	3,034	3,034	3,116	3,116	3,116
Offset b	No	Yes	Yes	No	Yes	Yes
Company FE	No	No	Yes	No	No	Yes

Panel C: Dynamics before the VC exit

	(1)	(2)	(3)	(4)	(5)	(6)
	Originality	Originality	Originality	Generality	Generality	Generality
Event Year -3	1.067**	1.070**	1.042	0.995	0.985	1.018
	(0.032)	(0.029)	(0.038)	(0.018)	(0.016)	(0.017)
Event Year -2	1.025	1.032	1.066**	0.996	1.007	1.033**
	(0.029)	(0.026)	(0.030)	(0.015)	(0.017)	(0.014)
Event Year -1	1.015	1.023	1.073***	1.007	0.995	1.012
	(0.022)	(0.020)	(0.024)	(0.011)	(0.010)	(0.012)
Event Year +1	1.043**	1.051***	1.020	0.998	1.011	0.995
	(0.021)	(0.019)	(0.019)	(0.012)	(0.010)	(0.011)
Event Year +2	1.029	1.037*	1.015	0.977	0.989	0.973**
	(0.022)	(0.020)	(0.022)	(0.015)	(0.012)	(0.012)
Event Year +3	1.033	1.046*	0.991	0.993	1.012	0.972*
	(0.028)	(0.026)	(0.025)	(0.016)	(0.015)	(0.014)
Event Year +4	1.082***	1.093***	1.026	0.990	1.019	0.985
	(0.028)	(0.027)	(0.032)	(0.016)	(0.015)	(0.016)
Event Year +5	1.059*	1.080***	0.977	0.974	0.981	0.958*
	(0.031)	(0.032)	(0.034)	(0.022)	(0.019)	(0.022)
Constant	0.559***	1.074***	1.237***	0.838***	1.138***	1.351***
	(0.009)	(0.016)	(0.026)	(0.007)	(0.009)	(0.015)
Observations	12,631	12,630	12,630	13,245	13,245	13,245
N. companies	2,670	2,670	2,670	2,776	2,776	2,776
Offset b_t	No	Yes	Yes	No	Yes	Yes
Company FE	No	No	Yes	No	No	Yes

Table 1.11 - VC and the rate of innovative activity: exploiting the 1999 legislative amendment in Texas

The table contains OLS regression estimates using the subsample of 341 companies headquartered in either the state of Texas (193) or one of its neighboring states: Colorado (119) , Louisiana (6), New Mexico (14) and Oklahoma (9) (note that there are no companies in Arkansas in the sample). An observation is a company-year. The dependent variable is the logarithm of successful patent applications (plus 1). *After VC* is an indicator variable that equals 1 after VC investment. *After 1999* is a dummy that equals 1 after 1999 for all observations of companies headquartered in Texas and 0 otherwise. The models include company and year fixed effects. Standard errors are clustered at the state level. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	OLS	Reduced Form	IV 2SLS
	(1)	(2)	(3)
After VC	0.250***		4.333**
	(0.029)		(1.761)
After 1999		1.305***	
		(0.453)	
Constant	-0.093	-0.747***	
	(0.115)	(0.178)	
First Stage			0.301***
After 1999			(0.035)
F-statistic			11.35
Observations			
N. Companies	341	341	341
Year FE	Yes	Yes	Yes
Company FE	Yes	Yes	Yes

Table 1.12 - VC and the quality of innovative activity: exploiting the 1999 Legislative amendment in Texas

The table contains linear regression estimates using the subsample of 669 patents filed by 265 companies before 2005 and that are headquartered in either the state of Texas (144) or one of its neighboring states: Colorado (100) , Louisiana (6) , New Mexico (8) and Oklahoma (7) (note that there are no companies in Arkansas in the sample). An observation is a patent. The dependent variable is the logarithm of scaled citations (plus 1). The type of citation used in the regressions is reported n top of each column. *After VC* is an indicator variable that equals 1 after VC investment. *After 1999* is a dummy that equals 1 after 1999 for all observations of companies headquartered in Texas and 0 otherwise. The models include company fixed effects. Standard errors are clustered at the state level. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	Scaled cites			Scaled self- cites			Scaled non-self- cites		
	OLS	Reduced Form	IV 2SLS	OLS	Reduced Form	IV 2SLS	OLS	Reduced Form	IV 2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
After VC	-0.229		-0.650***	-0.466*		-1.342***	-0.186		-0.533***
	(0.118)		(0.000)	(0.181)		(0.000)	(0.098)		(0.000)
After 1999		-0.275***			-0.569***			-0.226***	
		(0.000)			(0.000)			(0.000)	
Constant		0.844***		0.854***	0.642***		0.903***	0.817***	1.439***
		(0.000)		(0.139)	(0.000)		(0.076)	(0.000)	(0.000)
First Stage			0.424***						
After 1999			(0.000)						
F-stat.			24.30						
Obs.	669	669	669	669	669	669	669	669	669
N. Comp.	265	265	265	265	265	265	265	265	265
Offset b	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Comp. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.1 - Summary statistics analysis sample

The sample consists of 2,336 patents filed by 752 VC-backed companies at least two years before they were first financed by a VC (347 VC firms). For Panel B I use the state of the company as reported in the VentureXpert database. For Panels B, C, D and E the percentage of companies used for comparisons consists of 5,108 VC-backed companies that patent from the full matched sample, and of 20,058 companies included in the VentureXpert database between 1976 and 2009 (See Appendix 1 for details). The industry classification used in Panel D is based on the VentureXpert files.

Panel A. Application and grant years of patents, and transaction years for the VC investments

Year	Patent Applications	Patent Grants	VC investments
1976	144	3	
1977	78	73	
1978	84	85	3
1979	69	66	6
1980	45	67	10
1981	48	73	28
1982	47	37	15
1983	46	37	14
1984	62	52	15
1985	71	52	8
1986	44	70	17
1987	56	64	20
1988	70	53	12
1989	70	77	15
1990	66	62	16
1991	74	59	16
1992	92	61	13
1993	95	71	9
1994	99	80	18
1995	139	93	24
1996	117	78	38
1997	188	85	36
1998	207	132	67
1999	117	152	56
2000	126	160	86
2001	82	148	55
2002		107	77
2003		96	78
2004		51	
2005		45	
2006		30	
2007		9	
2008		8	
Total	2,336	2,336	752

Panel B. Distribution by state of companies and associated patents: top states in the analysis sample

	% of Companies			% of Patents	
State	Analysis Sample	Full Matched Sample	Overall VC Population	Analysis Sample	Full Matched Sample
CA	34.97%	44.4%	38.8%	32.6%	56.5%
CO	2.39%	2.7%	2.9%	3.6%	1.2%
CT	2.66%	1.7%	1.6%	3.3%	0.8%
IL	2.53%	1.9%	2.2%	2.1%	0.6%
MA	14.10%	12.8%	10.8%	10.5%	9.0%
NJ	2.66%	2.6%	2.5%	2.3%	1.1%
NY	3.99%	2.9%	5.3%	3.4%	1.8%
PA	3.46%	3.1%	3.4%	5.0%	2.2%
TX	5.32%	4.8%	5.7%	9.7%	5.9%
WA	2.66%	2.9%	3.2%	1.9%	10.7%

Panel C. Distribution of companies by type of VC investment

		% of Companies		
	# of companies	Analysis Sample	Full matched Sample	Overall VC Population
Bridge Loan	21	2.8%	1.7%	2.4%
Early Stage	257	34.2%	38.2%	39.8%
Expansion	299	39.8%	25.3%	25.7%
Later Stage	91	12.1%	7.0%	5.9%
Seed	84	11.2%	27.8%	26.1%
Total	752			

Panel D. Distribution of companies by type of VC exit

		% of Companies		
	# of companies	Analysis Sample	Full matched Sample	Overall VC Population
Acquisition	282	37.5%	34.9%	30.8%
Active	209	27.8%	29.9%	35.8%
Bankruptcy	9	1.2%	1.3%	1.3%
Defunct	140	18.6%	14.4%	19.9%
Merger	10	1.3%	1.6%	1.6%
Other	11	1.4%	1.7%	1.6%
Went Public	91	12.1%	16.3%	9.1%
Total	752			

Panel E. Industry distribution of companies and patents

		% of Companies				% of Patents	
	# of companies	Analysis sample	Full matched sample	Overall VC Population	# of patents	Analysis sample	Full matched sample
Biotechnology	63	8.4%	9.9%	6.1%	199	8.5%	11.6%
Comm. and Media	75	10.0%	11.0%	10.3%	215	9.2%	8.9%
Computer Hardware	51	6.8%	8.9%	6.3%	104	4.5%	17.2%
Computer Software	94	12.5%	16.3%	21.3%	180	7.7%	13.6%
Consumer Related	33	4.4%	2.0%	4.8%	125	5.4%	1.1%
Industrial Energy	97	12.9%	8.0%	5.1%	377	16.1%	4.4%
Internet Specific	37	4.9%	8.5%	20.7%	50	2.1%	2.0%
Medical Health	145	19.3%	16.8%	11.6%	505	21.6%	15.1%
Other Products	30	4.0%	2.6%	6.6%	101	4.3%	0.8%
Semiconductors	127	16.9%	16.0%	7.2%	480	20.5%	25.3%
Total	752				2,336		

Panel F. Distribution of patent age the year of the VC investment

	Number of patents	Percentage of sample
2 Years	462	19.78
3 Years	643	27.53
4 Years	325	13.91
5 Years	210	8.99
Between 6 years and 10 years	411	17.59
More than 10 years	285	12.19
Total	2,336	

Panel G. Annual citations (excluding self-citations)

	Citation type	Baseline state-level	Mean	S. D.	Med.	Min	Max	Obs.
Patents	All		0.92	2.45	0.00	0.00	60.00	43,519
Citation Baseline	All	No	0.63	0.77	0.39	0.00	13.50	43,519
Citation Baseline	All	Yes	0.61	1.14	0.25	0.00	32.00	43,519
Patents	Out-state		0.75	2.01	0.00	0.00	43.00	46,519
Citation Baseline	Out-state	Yes	0.49	0.96	0.20	0.00	29.00	46,519

Table 2.2 - Summary statistics restricted sample 1993-2008

Information on public state pension funds' assets from the Census Bureau is only available from 1993 to 2008. The sample restricted to VC investments during this period consists of 1,657 patents filed by 517 VC-backed companies. For Panel B, I use the state of the company as reported in the VentureXpert database. Pension Funds' Assets is the value of the assets held by local and state pension funds deflated and expressed in billions of 1982 U.S. dollars.

Panel A. Application and grant years of patents and transaction years for the VC

Year	Patent Applications	Patent Grants	VC investments
1976	29		
1977	16	14	
1978	19	20	
1979	16	13	
1980	10	18	
1981	12	14	
1982	18	8	
1983	15	8	
1984	25	21	
1985	25	17	
1986	23	30	
1987	27	26	
1988	39	21	
1989	48	38	
1990	29	42	
1991	50	29	
1992	86	36	
1993	95	45	
1994	99	70	
1995	139	88	13
1996	117	77	18
1997	188	85	25
1998	207	132	44
1999	117	151	49
2000	126	160	81
2001	82	148	53
2002		107	74
2003		96	77
2004		51	
2005		45	
2006		30	
2007		9	
2008		8	
Total	1,657	1,657	517

Panel B. Distribution of public pension funds' assets, companies and patents by state

	Pension Assets		% of Patents		% of Companies	
	Mean	Std. dev.	Restricted sample	Analysis sample	Restricted sample	Analysis sample
AL	17.17	1.45	0.60%	0.40%	0.40%	0.30%
AZ	19.87	3.48	1.80%	1.80%	1.00%	1.60%
CA	284.37	64.69	37.00%	32.60%	37.30%	35.00%
CO	21.67	5.06	3.10%	3.60%	2.30%	2.40%
CT	15.17	3.06	2.70%	3.30%	2.30%	2.70%
DC	3.26	0.81	0.40%	0.30%	0.20%	0.10%
FL	71.01	16.19	1.90%	2.00%	1.90%	2.00%
GA	35.36	8.79	1.10%	1.30%	1.90%	2.00%
ID	5.06	0.95	0.90%	0.70%	0.40%	0.40%
IL	63.77	14.25	2.10%	2.10%	2.10%	2.50%
IN	14.25	2.09	0.10%	0.20%	0.20%	0.40%
KS	6.79	1.91	0.10%	0.20%	0.20%	0.10%
LA	17.67	3.99	0.80%	0.60%	0.60%	0.40%
MA	29.68	7.12	7.80%	10.50%	12.00%	14.10%
MD	26.89	4.89	3.30%	3.40%	2.30%	2.40%
ME	4.98	1.59	0.30%	0.20%	0.20%	0.10%
MI	48.45	7.78	0.80%	1.20%	1.40%	1.60%
MN	28.79	5.21	1.20%	1.30%	2.10%	2.30%
MO	28.27	5.12	0.40%	0.70%	0.60%	0.90%
NC	39.50	6.05	1.20%	0.80%	2.10%	1.50%
NE	4.82	1.11	0.20%	0.20%	0.20%	0.10%
NH	2.81	0.84	0.80%	1.20%	1.20%	1.50%
NJ	36.51	6.14	2.70%	2.30%	2.70%	2.70%
NM	10.42	2.48	0.50%	0.30%	0.60%	0.40%
NV	9.47	3.18	0.10%	0.00%	0.20%	0.10%
NY	177.14	35.43	3.80%	3.40%	4.60%	4.00%
OH	80.36	12.57	2.30%	2.20%	1.70%	1.90%
OR	27.04	7.99	0.40%	1.90%	0.60%	0.70%
PA	58.90	10.68	2.90%	5.00%	3.10%	3.50%
RI	4.49	1.51	0.10%	0.10%	0.40%	0.30%
SC	14.78	2.91	0.10%	0.20%	0.20%	0.30%
TN	20.31	3.82	2.20%	2.00%	0.60%	0.80%
TX	90.55	21.93	12.20%	9.70%	6.40%	5.30%
UT	9.51	2.35	0.30%	0.70%	0.80%	0.80%
VA	30.84	6.57	0.80%	0.90%	1.40%	1.20%
VT	1.53	0.40	0.30%	0.30%	0.20%	0.30%
WA	32.06	5.81	2.20%	1.90%	3.10%	2.70%
WI	44.96	7.34	0.20%	0.30%	0.40%	0.40%
WY	2.85	0.81	0.30%	0.20%	0.20%	0.10%

Panel C. Distribution of companies by type of VC investment

	Number of Companies	Percentage of sample: Restricted Sample	Percentage of sample: Analysis Sample
Bridge Loan	16	3.1%	2.8%
Early Stage	209	40.4%	34.2%
Expansion	192	37.1%	39.8%
Later Stage	57	11.0%	12.1%
Seed	43	8.3%	11.2%
Total	517		

Panel D. Industry distribution of companies and patents

	# of companies	% of Companies: Restricted Sample	% of Companies: Analysis Sample	# of patents	% of Patents: Restricted Sample	% of Patents: Analysis Sample
Biotechnology	55	10.6%	8.4%	179	10.8%	8.5%
Comm. and Media	52	10.1%	10.0%	170	10.3%	9.2%
Computer Hardware	27	5.2%	6.8%	58	3.5%	4.5%
Computer Software	72	13.9%	12.5%	141	8.5%	7.7%
Consumer Related	17	3.3%	4.4%	79	4.8%	5.4%
Industrial Energy	42	8.1%	12.9%	218	13.2%	16.1%
Internet Specific	36	7.0%	4.9%	46	2.8%	2.1%
Medical Health	109	21.1%	19.3%	362	21.9%	21.6%
Other Products	21	4.1%	4.0%	67	4.0%	4.3%
Semiconductors	86	16.6%	16.9%	337	20.3%	20.5%
Total	517			1,657		

Panel E. Distribution of companies by type of VC exit

	Number of companies	% of Companies: Restricted Sample	% of Companies: Analysis Sample
Acquisition	185	35.8%	37.5%
Active	184	35.6%	27.8%
Bankruptcy	8	1.6%	1.2%
Defunct	77	14.9%	18.6%
Merger	4	0.8%	1.3%
Other	7	1.4%	1.4%
Went Public	52	10.1%	12.1%
Total	517		

Panel F. Distribution of patent age the year of the VC investment

	Number of patents	Percentage of sample
2 Years	329	28.12
3 Years	425	34.79
4 Years	220	15.9
5 Years	132	9.06
Between 6 years and 10 years	298	12.14
More than 10 years	253	
Total	1,657	

Panel G. Annual citations (excluding self-citations)

	Citation type	Baseline state-level	Mean	S. D.	Med.	Min	Max	Obs.
Patents	All		1.21	2.97	0.00	0.00	60.00	21,757
Citation Baseline	All	No	0.82	0.92	0.56	0.00	11.47	21,757
Citation Baseline	All	Yes	0.84	1.39	0.41	0.00	28.69	21,757
Patents	Out-state		0.97	2.40	0.00	0.00	43.00	21,757
Citation Baseline	Out-state	Yes	0.66	1.15	0.31	0.00	25.67	21,757

Table 2.3 – Univariate tests VC investments and patent citations

This table compares average annual citations to patents to the average annual citation baseline before and after the VC investment. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level.

	Annual Average			
	Pre-VC	Post-VC	Difference	Ratio
Citations	0.64	1.04	0.40***	1.63
	(1.69)	(2.69)		
Citation Baseline	0.54	0.66		
	(0.61)	(0.83)		
Difference	0.10***	0.37***		
			Difference in Difference	Ratio of Ratios
			0.28***	1.33

Table 2.4 - Poisson regressions VC investments and patent citations

The table contains Poisson regression estimates. An observation is a patent-year. The dependent variable is annual citations. VC_{pt} is an indicator variable that equals 1 after VC investment. b_t corresponds to average citations received at year t by matching patents in the same technology-class and with the same application-year. The Poisson model requires that annual average citations to matching patents be different from zero, which explains the difference in observations across columns (1)-(2). The fixed-effects Poisson model requires variation in the dependent variable for each patent, which explains the difference in observations across columns (2), and, (3). The reported coefficients are incidence rates. A coefficient greater than one corresponds to a positive relationship between the explanatory variable and the citation intensity. Standard errors are clustered at the issuing company level. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)
Model	Poisson	Poisson	Poisson
VC_{pt}	1.627***	1.328***	1.189***
	(0.106)	(0.063)	(0.045)
Constant	0.636***	1.177***	
	(0.038)	(0.050)	
Observations	43,519	41,172	38,981
Number of patents	2,336	2,336	2,183
Number of companies	752	752	723
Offset b_t	No	Yes	Yes
Patent FE	No	No	Yes

Table 2.5 - VC investments and state pension funds' assets

The table reports the relation between investments by VC firms and pension funds' assets in their home-state. Observations are at the state-year level. The dependent variable is stated at the beginning of each column. Investments correspond to the value of investments made by VC firms (in billions 1982 U.S dollars). Local Investments correspond to the value of investments made by VC firms in local companies (in billions 1982 U.S dollars). New Investments correspond to the value of investments made by VC firms in new companies (in billions 1982 U.S dollars). Standard errors are clustered at the state level. $Pension$ corresponds to the value of assets held by local and state pension funds in 1982 billion U.S. dollars and lagged by 1 year. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Investments	Local Investments	Non-local Investments	New Investments	New Local Investments	Non-local New Investments
$Pension$	0.052***	0.036**	0.016***	0.013***	0.009**	0.004***
	(0.016)	(0.014)	(0.003)	(0.004)	(0.003)	(0.001)
Constant	-1.502**	-1.126**	-0.376***	-0.401**	-0.291**	-0.109***
	(0.591)	(0.486)	(0.114)	(0.157)	(0.131)	(0.028)
Obs.	765	765	765	765	765	765
$State$ F.E.	Yes	Yes	Yes	Yes	Yes	Yes
$Year$ F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.6 - IV analysis VC investments and patent citations

This table contains Poisson and Linear regression coefficients of the IV analysis. An observation is a patent-year. The dependent variable is indicated on top of each column. The instrument used in each model is indicated on top of each column. Scaled-cites corresponds to the number of citations a patent receives divided by the average number of citations received by matching patents in the same technology-class and filed the same year as the patent. VC_{pt} is a dummy variable that equals one after the VC investment. $Pension$ corresponds to the value of assets held by local and state pension funds in the home-state of the company expressed in 1982 billion U.S. dollars, lagged by 1 year. $Pension\_Norm$ corresponds to the value of assets held by local and state pension funds in the home-state of the company expressed 1982 billion U.S. dollars, normalized by average state GDP, and lagged by 1 year. $\Delta Pension$ corresponds to the value of assets held by local and state pension funds in the home-state of the company expressed in 1982 billion U.S. dollars, lagged by 1 year, and demeaned by time. b_t corresponds to average citations received at year t by matching patents in the same technology-class and with the same application-year. The estimated coefficients for columns (1)-(4) are incidence rates, except for the estimated coefficient of the first-stage. For the incidence rates a coefficient greater than one corresponds to a positive relationship between the explanatory variable and the citation intensity. Standard errors are clustered at the state level. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	Cites	Cites	Cites	Cites	Scaled-cites	Scaled-cites	Scaled-cites	Scaled-cites
Instrument		$Pension$	$Pension\_Norm$	$\Delta Pension$		$Pension$	$Pension\_Norm$	$\Delta Pension$
Model	Poisson	GMM-IV	GMM-IV	GMM-IV	OLS	2SLS	2SLS	2SLS
VC_{pt}	1.171***	1.495***	1.318	1.564***	0.225*	0.607***	0.524*	0.683***
	(0.069)	(0.199)	(0.239)	(0.179)	(0.132)	(0.218)	(0.272)	(0.187)
First Stage						0.006***	2.409**	0.006***
						(0.001)	(0.969)	(0.001)
F-test						31.13	6.187	84.46
Obs.	15,622	15,622	15,622	15,622	18,928	18,928	18,928	18,928
# patents	1,487	1,487	1,487	1,487	1,657	1,657	1,657	1,657
# comp.	491	491	491	491	517	517	517	517
# states	38	38	38	38	39	39	39	39
Offset b_t	Yes	Yes	Yes	Yes				
Patent FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.7 - First robustness check IV analysis VC investments and patent citations

This table contains Poisson and Linear regression coefficients of the IV analysis. An observation is a patent-year. The dependent variable is indicated on top of each column. The instrument used in each model is indicated on top of each column. Scaled Cites corresponds to the number of citations a patent receives divided by the average number of citations received by matching patents in the same technology-class, with the same application-year and issued in the same state as the patent. VC_{pt} is a dummy variable that equals one after the VC investment. $Pension$ corresponds to the value of assets held by local and state pension funds in the home-state of the company expressed in 1982 billion U.S. dollars, lagged by 1 year. $Pension\_Norm$ corresponds to the value of assets held by local and state pension funds in the home-state of the company expressed 1982 billion U.S. dollars, normalized by average state GDP, and lagged by 1 year. $\Delta Pension$ corresponds to the value of assets held by local and state pension funds in the home-state of the company expressed in 1982 billion U.S. dollars, lagged by 1 year, and demeaned by time. b_t corresponds to average citations received at year *t* by matching patents in the same technology-class, with the same application-year and issued in the same state. The estimated coefficients for columns (1)-(4) are incidence rates, except for the estimated coefficient of the first-stage. For the incidence rates a coefficient greater than one corresponds to a positive relationship between the explanatory variable and the citation intensity. Standard errors are clustered at the company level. Standard errors for the First Stage are clustered at the state level. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level.

	(1)	(2)	(3)	(4)	(4)	(5)	(6)	(7)
Dep. Var.	Cites	Cites	Cites	Cites	Scaled Cites	Scaled Cites	Scaled Cites	Scaled Cites
Instrument		$Pension$	$Pension\_Norm$	$\Delta Pension$		$Pension$	$Pension\_Norm$	$\Delta Pension$
Model	Poisson	GMM-IV	GMM-IV	GMM-IV	OLS	2SLS	2SLS	2SLS
VC_{pt}	1.258***	1.435**	1.428**	1.513**	0.277**	0.485**	0.435*	0.506**
	(0.067)	(0.219)	(0.223)	(0.263)	(0.123)	(0.215)	(0.256)	(0.230)
First Stage						0.007***	3.066	0.007***
						(0.001)	(8.818)	(0.001)
F-test						41.50	12.09	92.86
Obs.	11,726	11,726	11,726	11,726	14,820	14,810	14,810	14,810
# patents	1,288	1,288	1,288	1,288	1,513	1,503	1,503	1,503
# comp.	456	456	456	456	490	490	490	490
# states	32	32	32	32	32	32	32	32
Offset b_t	Yes	Yes	Yes	Yes				
Patent FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.8 - Second robustness check IV analysis VC investments and patent citations

This table contains Poisson and Linear regression coefficients of the IV analysis. An observation is a patent-year. The dependent variable is indicated on top of each column. The instrument used in each model is indicated on top of each column. Scaled out-of-state-cites corresponds to the number of citations a patent receives from assignees in a different state divided by the average number of out-of-state citations received by matching patents in the same technology-class, with the same application-year and issued in the same state as the patent. VC_{pt} is a dummy variable that equals one after the VC investment. $Pension$corresponds to the value of assets held by local and state pension funds in the home-state of the company expressed in 1982 billion U.S. dollars, lagged by 1 year. $Pension\_Norm$ corresponds to the value of assets held by local and state pension funds in the home-state of the company expressed in 1982 billion U.S. dollars, normalized by average state GDP, and lagged by 1 year. $\Delta Pension$corresponds to the value of assets held by local and state pension funds in the home-state of the company expressed in 1982 billion U.S. dollars, lagged by 1 year, and demeaned by time. b_t corresponds to average citations received at year *t* by matching patents in the same technology-class, with the same application-year and issued in the same state. The estimated coefficients for columns (1)-(4) are incidence rates, except for the estimated coefficient of the first-stage. For the incidence rates a coefficient greater than one corresponds to a positive relationship between the explanatory variable and the citation intensity. Standard errors are clustered at the company level. Standard errors for the First Stage are clustered at the state level. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	Out-of-state cites	Out-of-state cites	Out-of-state cites	Out-of-state cites	Scaled out-of-state cites	Scaled out-of-state cites	Scaled out-of-state cites	Scaled out-of-state cites
Ins.		$Pension$	$Pension\_Norm$	$\Delta Pension$		$Pension$	$Pension\_Norm$	$\Delta Pension$
Model	Poisson	GMM-IV	GMM-IV	GMM-IV	OLS	2SLS	2SLS	2SLS
VC_{pt}	1.292***	1.384**	1.451***	1.457**	0.310**	0.670**	0.614**	0.704**
	(0.065)	(0.214)	(0.205)	(0.262)	(0.123)	(0.262)	(0.276)	(0.286)
First Stage						0.006***	3.061***	0.007***
						(0.001)	(0.902)	(0.001)
F-test						43.70	11.56	101.67
Obs.	11,020	11,020	11,020	11,020	14,566	14,566	14,566	14,566
# patents	1,223	1,223	1,223	1,223	1,500	1,500	1,500	1,500
# comp.	447	447	447	447	490	490	490	490
# states	31	31	31	31	32	32	32	32
Offset b_t	Yes	Yes	Yes	Yes				
Patent FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.9 - Originality

This table reports Originality and Relative Originality measures for patents that are funded in hot versus cold markets. A patent is said to have been financed in a hot market if the size of local public pension funds' assets in the home-state of the company is above the 75th percentile of the state's average the year of the VC investment. Analogously, a patent is said to have been financed in a cold market if the size of local public pension funds' assets in the home-state of the company is below the 25th percentile of the state's average the year of the VC investment. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level.

	Hot Market Top 75%	Cold Market Bottom 25%	Difference
Originality	0.55	0.37	0.18***
Originality Adjusted	0.64	0.45	0.18***
Relative Originality	0.15	0.09	0.06***
Relative Originality Adjusted	0.15	0.10	0.06**

Table 2.10 - Univariate Tests VC investments and patent citations inside and outside VC portfolios

Panel A compares average annual portfolio-linked citations to patents to the average annual portfolio-linked citation baseline before and after the VC investment. Panel B compares average annual non-portfolio-linked citations to patents to the annual average non-portfolio-linked citation baseline before and after the VC investment. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level.

Panel A. Portfolio-Linked Citations

	Annual Average			
	Pre-VC	Post-VC	Difference	Ratio
Citations	0.002	0.008	0.006***	4.05
	(0.08)	(0.15)		
Citation Baseline	0.001	0.003	0.002***	2.75
	(0.61)	(0.83)		
Difference	0.001	0.005***		
Ratio	2.17	2.88		
			Difference in Difference	Ratio of Ratios
			0.004***	1.47

Panel B. Non-Portfolio-Linked Citations

	Annual Average			
	Pre-VC	Post-VC	Difference	Ratio
Citations	0.64	1.03	0.39***	1.62
	(1.68)	(2.68)		
Citation Baseline	0.54	0.66	0.12***	1.22
	(0.61)	(0.83)		
Difference	0.11***	1.37***		
Ratio	1.19	1.56		
			Difference in Difference	Ratio of Ratios
			0.27***	1.33

Table 2.11 - Poisson regressions VC investments and patent citations inside and outside VC portfolios

The table presents Poisson estimates where the effect of VC financing is allowed to affect differently citations that originate inside or outside VC portfolios. An observation is at the patent, year, and type of citation level. The dependent variable is annual citations. $Portfolio - linked$ ($Non - portfolio - linked$) is a dummy that equals one if the type of citation is portfolio- linked (non portfolio- linked). VC_{pt} is a dummy that equals one after the VC investment. b_{tC} corresponds to average citations of type C, where $C = \{Portfolio - linked, Non - portfolio - linked$, received at year *t* by matching patents in the same technology-class and with the same application-year. The Poisson model requires that annual average citations to matching patents be different from zero, which explains the difference in observations across columns (1)-(2). The fixed-effects Poisson model requires variation in the dependent variable for each patent-type of citation group for estimation, which explains the difference in observations across columns (2), and, (3). The reported coefficients are incidence rates. A coefficient greater than one corresponds to a positive relationship between the explanatory variable and the citation intensity. Standard errors are clustered at the patent level and reported in parenthesis. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)
Model	Poisson	Poisson	Poisson
A. Estimated Coefficients			
$Non - Portfolio - linked$	0.635***	1.176***	
	(0.024)	(0.040)	
$Portfolio - linked$	0.002***	0.868	
	(0.001)	(0.497)	
$VC_{pt} * Non - Portfolio - linked$ (I)	1.620***	1.325***	1.186***
	(0.067)	(0.050)	(0.035)
$VC_{pt} * Portfolio - linked$ (II)	4.052***	2.437	2.785**
	(1.619)	(1.541)	(1.276)
B. Difference in Coefficients			
Chi2	5.37	0.93	3.44
p- value Chi2 test	(0.03)	(0.34)	(0.06)
Observations	87,038	45,064	39,299
# of patents	2,336	2,336	2,183
# of companies	752	752	726
Offset b_{tC}	No	Yes	Yes
Patent-type of citation FE	No	No	Yes

Table 2.12 - IV analysis VC investments and patent citations inside and outside VC portfolios

This table contains Poisson and Linear regression coefficients of the IV analysis. The dependent variable is indicated on top of each column. An observation is at the patent- year level. VC_{pt} is a dummy that equals one after the VC investment. b_{tC} corresponds to average citations of type C, where C is either portfolio- or non portfolio-linked citations, received at year t by matching patents in the same technology-class and with the same application-year. The GMM-IV and 2SLS specifications use $Pension$, the size of local and state pension funds' real assets in the home-state of the company lagged by one year, to instrument VC_{pt}. For columns (1)-(4) standard errors are clustered at the patent level and reported in parenthesis. For columns (5)-(8) standard errors are clustered at the state level and reported in parenthesis. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	Portfolio-linked cites	Portfolio-linked cites	Portfolio-linked scaled cites	Portfolio-linked scaled cites	Non-portfolio-linked cites	Non-portfolio-linked cites	Non-portfolio-linked scaled cites	Non-portfolio-linked scaled cites
Model	Poisson	GMM-IV	OLS	2SLS	Poisson	GMM-IV	OLS	2SLS
VC_{pt}	2.390*	6.274	1.361	5.113	1.167***	1.463***	0.224*	0.596***
	(1.228)	(14.289)	(1.908)	(3.747)	(0.039)	(0.191)	(0.132)	(0.215)
First Stage				0.007***				0.006***
				(0.000)				(0.001)
F test				437.56				31.13
Obs.	115	115	2,617	2,513	15,622	15,622	18,928	18,928
# patents	15	15	590	486	1,487	1,487	1,657	1,657
# comp.	9	9	235	235	491	491	517	517
# states	3	3	25	25	38	38	39	39
Offset b_{tC}	Yes	Yes			Yes	Yes		
Patent FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.13 - Univariate Tests VC investments and inventor and non-inventor-linked citations

The table presents average annual inventor- and non-inventor- linked citations. Panel A, reports citations from all assignees. Panel B, reports portfolio-linked citations. Panel C reports non portfolio-linked citations. Column (5) presents the ratio between average annual non- inventor-linked citations post VC-investment, and average annual citations pre VC-investment for patents. Column (6) presents the "ratio of ratios" defined as the ratio between the ratio of average annual non- inventor-linked citations post and pre VC-financing for patents, to the ratio of average annual non-inventor-linked citations post and pre VC-financing for matching patents. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level.

Panel A. All Citations

	Average Annual Citations				Average Annual Citation Baseline				Ratio	Ratio of Ratios
	Pre-VC		Post-VC		Pre-VC		Post-VC			
	(1)		(2)		(3)		(4)		(5)	(6)
Non- inventor-linked	0.64	[1.69]	0.97	[2.53]	0.54	[0.61]	0.58	[0.83]	1.52	1.411
Inventor-linked			0.07	[0.56]			0.08	[0.14]		

Panel B. Portfolio-linked Citations

	Average Annual Citations				Average Annual Citation Baseline				Ratio	Ratio of Ratios
	Pre-VC		Post-VC		Pre-VC		Post-VC			
	(1)		(2)		(3)		(4)		(5)	(6)
Non-inventor -linked	0.0020	[0.08]	0.0076	[0.14]	0.0009	[0.08]	0.0024	[0.02]	3.87	1.459
Inventor-linked			0.0004	[0.03]			0.0004			

Panel C. Non-Portfolio-linked Citations

	Average Annual Citations				Average Annual Citation Baseline				Ratio	Ratio of Ratios
	Pre-VC		Post-VC		Pre-VC		Post-VC			
	(1)		(2)		(3)		(4)		(5)	(6)
Non-inventor-linked	0.63	[1.68]	0.96	[2.52]	0.54	[0.61]	0.58	[0.72]	1.52	1.408
Inventor-linked			0.07	[0.55]			0.08			

Table 2.14 - Poisson regressions VC investments and non-inventor-linked citations inside and outside VC portfolios

The table presents Poisson regression coefficients where the effect of the VC investment is allowed to affect differently non-inventor-linked citations that originate inside or outside VC portfolios. An observation is at the patent, year, and type of citation level. The dependent variable is annual non-inventor-linked citations. $Portfolio - linked$ ($Non - portfolio - linked$) is a dummy that equals one if the type of citation is portfolio-linked (non portfolio-linked). VC_{pt} is a dummy that equals one after the VC investment. b_{tC} corresponds to average citations received at year t by matching patents of citations type C, where $C = \{Portfolio - linked,\ Non - portfolio - linked\}$. The Poisson model requires that annual average citations to matching patents be different from zero, which explains the difference in observations across columns (1)-(2). The fixed-effects Poisson model requires variation in the dependent variable for each patent-type of citation group for estimation, which explains the difference in observations across columns (2), and, (3). The reported coefficients are incidence rates. A coefficient greater than one corresponds to a positive relationship between the explanatory variable and the citation intensity. Standard errors are clustered at the patent level and reported in parenthesis. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)
Model	Poisson	Poisson	Poisson
A. Estimated Coefficients			
$Non - Portfolio - linked$	0.635***	1.176***	
	(0.024)	(0.040)	
$Portfolio - linked$	0.002***	0.868	
	(0.001)	(0.497)	
$VC_{pt} * Non - Portfolio - linked$ (I)	1.517***	1.409***	1.281***
	(0.063)	(0.053)	(0.038)
$VC_{pt} * Portfolio - linked$ (II)	3.869***	2.620	2.891**
	(1.557)	(1.667)	(1.394)
B. Difference in Coefficients II-I			
Chi2	5.51	0.96	2.83
p- value Chi2 test	0.02	0.33	0.09
Observations	87,038	44,991	39,115
Number of patents	2,336	2,336	2,170
Number of companies	752	752	726
Offset b_{tC}	No	Yes	Yes
Patent-type of citation FE	No	No	Yes

Table 2.15 - IV analysis VC investments and non-inventor-linked citations inside and outside VC portfolios

This table contains linear regression coefficients of the instrumental variable analysis of non-inventor-linked inside and outside VC portfolios. The dependent variable is indicated on top of each column. An observation is at the patent-year level. VC_{pt} is a dummy that equals one after the VC investment. b_{tC} corresponds to average citations of type C, where C is either (non-inventor-linked) portfolio- or non-portfolio-linked citations, received at year t by matching patents in the same technology-class and with the same application-year. The GMM-IV and 2SLS specifications use $Pension$, the size of local and state pension funds' real assets in the home-state of the company lagged by one year, to instrument VC_{pt}. For columns (1)-(4) standard errors are clustered at the patent level and reported in parenthesis. For columns (5)-(8) standard errors are clustered at the state level and reported in parenthesis. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	Portfolio-linked cites	Portfolio-linked cites	Portfolio-linked scaled cites	Portfolio-linked scaled cites	Non-portfolio-linked cites	Non-portfolio-linked cites	Non-portfolio-linked scaled cites	Non-portfolio-linked scaled cites
Model	Poisson	GMM-IV	OLS	2SLS	Poisson	GMM-IV	OLS	2SLS
VC_{pt}	2.934	4.081	0.705	2.481*	1.274***	1.595***	0.325**	0.684***
	(2.021)	(14.374)	(0.581)	(1.493)	(0.076)	(0.235)	(0.140)	(0.227)
First Stage				0.007***		0.710***		0.006***
				(0.0003)		(0.13)		(0.001)
F-test				437.56		30.04		31.13
Obs.	109	109	2,617	2,513	15,516	15,516	18,928	18,928
# patents	15	15	590	486	1,475	1,475	1,657	1,657
# comp.	9	9	210	210	491	491	517	517
# states	3	3	24	24	38	38	39	39
Offset b_{tC}	Yes	Yes			Yes	Yes		
Patent FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.16 - Summary statistics patent sales

This table reports summary statistics of patent sales around the VC investment. Panel A reports number of patents that were sold before and after the VC investment. Panel B compares patents and matching patents and their respective likelihood of being sold at least once throughout the sample. Standard deviations are included in parenthesis. The number of observations is reported in squared brackets. Panel C compares average annual citations for patents and the citation baseline according to whether the patents were sold or not throughout the sample.

Panel A. Number of patents sold

	Number	Percentage of Total
Total patents sold during the sample	375	16%
Patents sold at least once before the VC investment	62	3%
Patents sold at least once after the VC investment	327	14%

Panel B. Annual Likelihood that a patent is traded (percentage)

Patents		Matching Patents		Diff.	Diff. in Diff.
Pre-VC	Post-VC	Pre-VC	Post-VC		
0.51	0.92	0.37	0.31	0.41***	0.477***
(7.12)	(10.21)	(0.75)	(0.60)		
[12,767]	[40,096]	[12,767]	[40,096]		

Panel C. Difference in citations to patents

	Annual Average Citations		Annual Average Citation Baseline		Diff.	Ratio	Diff.-in-Diff.	Ratio of Ratios
	Pre-VC	Post-VC	Pre-VC	Post-VC				
Sold	0.75	1.20	0.54	0.68	0.45***	1.61	0.31***	1.28
	(2.11)	(3.08)	(0.65)	(0.86)				
	[1,902]	[5,257]	[1,902]	[5,257]				
Not Sold	0.62	1.00	0.54	0.66	0.39***	1.62	0.27***	1.33
	(1.60)	(2.61)	(0.60)	(0.82)				
	[10,865]	[25,495]	[10,865]	[25,495]				
Sold - Not Sold	0.13***	0.20***	0.01	0.03***	0.07	-0.02	0.05	-0.05
	[12,767]	[30,752]	[12,767]	[30,752]				

Table 3.1 - Sample composition

This table uses a sample of 347,987 patent pairs, which includes 102,098 actual citations (taking g = 1), 102,098 JTH-style matched pairs and 143,791 additional pairs from citing classes and years not represented in the matched sample. The total number of cited (citing) patents is 13,072 (82,597).

Panel A: Distribution of application years for cited and citing patents and year of first VC investment

	Cited patents	Citing patents	Cited company	Citing company	Date Citation
1976	3	3	12	14	3
1977	3	6	13	19	6
1978	10	14	17	20	16
1979	14	28	15	27	30
1980	22	48	44	65	54
1981	39	69	81	111	93
1982	64	128	57	96	177
1983	83	175	79	108	274
1984	115	252	82	124	425
1985	139	304	65	100	596
1986	199	398	52	93	847
1987	290	518	71	119	1,234
1988	413	695	70	108	1,736
1989	488	864	81	142	2,464
1990	628	1,018	65	97	3,376
1991	704	1,239	39	55	4,462
1992	973	1,550	49	75	5,978
1993	1,127	1,931	68	85	8,357
1994	1,604	2,660	55	92	12,038
1995	2,331	4,282	83	172	18,778
1996	2,240	4,786	63	208	26,603
1997	1,437	6,213	43	238	31,775
1998	146	6,484	4	278	32,220
1999		7,257		319	34,904
2000		8,380		459	36,916
2001		8,352		290	33,968
2002		8,128		234	30,546
2003		6,069		218	22,873
2004		5,290		207	18,992
2005		3,411		158	11,042
2006		1,549		122	5,251
2007		472		88	1,807
2008		24		61	146
2009		3		22	3
Total	13,072	82,597	1,208	4,624	347,987

Panel B: Distribution across U.S. States of cited and citing patents

	Cited patent	Citing patent
AL	47	251
AR		1
AZ	78	452
CA	8,079	47,312
CO	163	982
CT	53	607
DC	4	61
DE	3	30
FL	61	567
GA	46	404
HI		5
IA	2	21
ID	3	53
IL	105	511
IN	45	211
KS		11
KY		6
LA	1	23
MA	1,039	7,313
MD	81	709
ME		12
MI	29	217
MN	391	2,560
MO	4	146
MS		14
MT		2
NC	33	656
ND		3
NE		16
NH	16	338
NJ	117	865
NM	3	47
NV	18	48
NY	186	1,355
OH	56	446
OK	5	52
OR	75	411
PA	225	1,314
RI	7	40
SC	2	17
SD		3
TN	6	150
TX	1,071	5,098
UT	11	154
VA	36	384
VT		23
WA	918	8,414
WI	53	281
WV		1
Total	13,072	82,597

Panel C: Distribution across technology classes of cited patents

	Citations		Patents	
	Number	%	Number	%
Chemical	23,222	6.67	1,074	8.22
Computers and Communications	140,888	40.49	5,614	42.95
Drugs and Medical	106,845	30.7	3,017	23.08
Electrical and Electronic	63,096	18.13	2,724	20.84
Mechanical	9,964	2.86	447	3.42
Others	3,972	1.14	196	1.5

Table 3.2 - Summary statistics

This table presents summary statistics of the main variables used in the regression models. The sample consists of 347,7987 patent pairs, which includes 102,098 actual citations (taking g = 1), 102,098 JTH-style matched pairs and 143,791 additional pairs from citing classes and years not represented in the matched sample. The total number of cited (citing) patents is 13,072 (82,597).

Variable	Observations	Mean	Std. Dev.	Min	Max
Citation	347,987	0.293	0.455	0	1.000
Portfolio link	347,987	0.178	0.382	0	1.000
Syndication link	347,987	0.497	0.500	0	1.000
Indirect link	347,987	0.166	0.372	0	1.000
Same class	347,987	0.230	0.421	0	1.000
Same state	347,987	0.389	0.488	0	1.000
Technological proximity	347,987	0.326	0.344	0	1.000
Geographical distance	344,774	2.183	2.373	0	18.987
Propensity	347,987	0.015	0.030	0	0.590
Portfolio link × Same state	347,987	0.074	0.263	0	1.000
Syndication link × Same state	347,987	0.231	0.421	0	1.000
Indirect link × Same state	347,987	0.036	0.186	0	1.000
Portfolio link × Technological proximity	347,987	0.075	0.206	0	1.000
Syndication link × Technological proximity	347,987	0.159	0.292	0	1.000
Indirect link × Technological proximity	347,987	0.054	0.194	0	1.000
Portfolio link × Geographical distance	344,774	0.344	1.232	0	17.177
Syndication link × Geographical distance	344,774	1.046	2.026	0	18.987
Indirect link × Geographical distance	344,774	0.421	1.305	0	16.967

Table 3.3 - Non parametric evidence

This table presents summary statistics of the main variables used in the regression models. The sample consists of 347,7987 patent pairs, which includes 102,098 actual citations (taking g = 1), 102,098 JTH-style matched pairs and 143,791 additional pairs from citing classes and years not represented in the matched sample. The total number of cited (citing) patents is 13,072 (82,597).

Panel A. VC proximity

	Cites	Control	Diff.	t-stat
Portfolio link	22.40%	21.52%	0.89%	4.849
Syndication link	49.5%	49.9%	-0.37%	-1.69
Indirect link	16.8%	15.2%	1.64%	10.12
Observations	102,098	102,098		

Panel B. VC and technological proximity

	Tech. distance <=p25				p25< Tech. distance <=p50			
	Cites	Control	Diff.	t-stat	Cites	Control	Diff.	t-stat
Portfolio link	12.04%	7.82%	4.22%	5.93	16.4%	14.2%	2.2%	5.71
Syndication link	42.0%	49.5%	-7.49%	-6.15	53.1%	56.8%	-3.7%	-6.84
Indirect link	22.1%	20.0%	2.12%	2.14	17.5%	15.8%	1.6%	4.01
Observations	2,599	4,639			13,172	23,853		

	p50< Tech. distance <=p75				p50< Tech. distance <=p75			
	Cites	Control	Diff.	t-stat	Cites	Control	Diff.	t-stat
Portfolio link	25.1%	25.6%	-0.5%	-1.71	22.6%	23.8%	-1.3%	-4.28
Syndication link	50.5%	48.7%	1.8%	4.83	48.3%	46.6%	1.7%	4.90
Indirect link	13.1%	13.4%	-0.4%	-1.53	19.2%	16.0%	3.2%	11.83
Observations	37,020	38,831			49,307	34,775		

Panel C. VC proximity and state borders

	Different State				Same State			
	Cites	Control	Diff.	t-stat	Cites	Control	Diff.	t-stat
Portfolio link	26.3%	20.7%	5.6%	22.51	17.8%	22.7%	-4.9%	-18.29
Syndication link	39.1%	43.1%	-4.0%	-13.62	61.9%	59.4%	2.5%	7.59
Indirect link	22.9%	20.2%	2.7%	10.94	9.6%	8.1%	1.5%	7.76
Observations	55,483	59,481			46,615	42,617		

Table 3.4 - Technological convergence in VC networks

This tables shows results of estimating weighted logistic regressions. The unit of observation is a pair of patents representing an actual or potential citation (control). The dependent variable is an indicator for whether or not the citing patent actually cited the cited patent. The regression model also uses a constant and a set of fixed-effects as indicated below, but these are not reported to conserve space. Robust standard errors are shown in parentheses, and are clustered on the cited patent. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Standard errors double clustered at the cited-company and citing-company levels are reported in squared brackets.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Same class		3.438***	3.413***	1.527***	1.531***	1.514***	1.525***
		(0.056)	(0.056)	(0.066)	(0.066)	(0.066)	(0.066)
		[0.172]	[0.175]	[0.195]	[0.196]	[0.193]	[0.196]
Same state		0.404***	0.276***	0.320***	0.766***	0.311***	0.315***
		(0.032)	(0.034)	(0.036)	(0.072)	(0.037)	(0.036)
		[0.168]	[0.170]	[0.111]	[0.201]	[0.108]	[0.109]
Citation propensity		10.793***	10.904***	5.518***	5.506***	5.554***	5.544***
		(0.935)	(0.938)	(1.093)	(1.101)	(1.085)	(1.091)
		[1.722]	[1.775]	[1.788]	[1.794]	[1.800]	[1.783]
Geographical distance			-0.082***	-0.070***	-0.069***	-0.072***	-0.106***
			(0.006)	(0.006)	(0.006)	(0.006)	(0.016)
			[0.014]	[0.013]	[0.013]	[0.013]	[0.035]
Technological proximity				4.735***	4.724***	5.174***	4.735***
				(0.051)	(0.053)	(0.081)	(0.051)
				[0.211]	[0.220]	[0.285]	[0.212]
Portfolio-link	1.389***	0.929***	0.919***	0.227***	0.527***	0.890***	0.145**
	(0.042)	(0.047)	(0.048)	(0.054)	(0.072)	(0.065)	(0.068)
	[0.272]	[0.239]	[0.238]	[0.171]	[0.217]	[0.234]	[0.183]
Syndication-link	0.635***	0.449***	0.450***	0.171***	0.407***	0.378***	0.089
	(0.033)	(0.036)	(0.036)	(0.042)	(0.055)	(0.044)	(0.054)
	[0.200]	[0.151]	[0.151]	[0.145]	[0.145]	[0.165]	[0.159]
Indirect-ink	0.531***	0.422***	0.432***	0.235***	0.331***	0.225***	0.225***
	(0.039)	(0.042)	(0.042)	(0.046)	(0.058)	(0.061)	(0.065)
	[0.239]	[0.195]	[0.193]	[0.126]	[0.157]	[0.178]	[0.140]
Interactions					**Same State**	**Tech. proximity**	**Geo. Distance**
Portfolio link×					-0.695***	-1.238***	0.044**
					(0.098)	(0.112)	(0.019)
					[0.269]	[0.320]	[0.038]
Syndication link×					-0.542***	-0.424***	0.044***
					(0.080)	(0.082)	(0.017)
					[0.221]	[0.238]	[0.035]
Indirect link×					-0.146	-0.042	0.010
					(0.097)	(0.103)	(0.021)
					[0.218]	[0.295]	[0.034]
Observations	347,786	347,786	344,573	344,573	344,573	344,573	344,573
Pseudo-R2	0.035	0.140	0.219	0.219	0.219	0.219	0.219
Prob.> chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Citation Lag FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Technology class FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lead VC Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 3.5 - Robustness check: excluding the state of California

This tables shows results of estimating weighted logistic regressions. The unit of observation is a pair of patents representing an actual or potential citation (control). The dependent variable is an indicator for whether or not the citing patent actually cited the cited patent. The regression model also uses a constant and a set of fixed-effects as indicated below, but these are not reported to conserve space. Robust standard errors are shown in parentheses, and are double clustered at the cited-company and citing-company level. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Same class	1.749***	1.753***	1.731***	1.749***
	(0.115)	(0.115)	(0.115)	(0.115)
	[0.190]	[0.192]	[0.189]	[0.190]
Same state	0.192**	-0.018	0.181*	0.197**
	(0.093)	(0.273)	(0.093)	(0.092)
	[0.157]	[0.562]	[0.156]	[0.158]
Citation propensity	5.196***	5.193***	5.165***	5.138***
	(1.935)	(1.948)	(1.930)	(1.937)
	[3.274]	[3.295]	[3.258]	[3.252]
Geographic distance	-0.042***	-0.041***	-0.042***	-0.007
	(0.009)	(0.009)	(0.009)	(0.024)
	[0.014]	[0.014]	[0.014]	[0.037]
Technology proximity	4.630***	4.628***	4.899***	4.630***
	(0.098)	(0.098)	(0.134)	(0.098)
	[0.246]	[0.244]	[0.320]	[0.247]
Portfolio link	0.595***	0.605***	1.180***	0.765***
	(0.096)	(0.099)	(0.122)	(0.122)
	[0.203]	[0.224]	[0.288]	[0.213]
Syndication link	0.470***	0.436***	0.473***	0.520***
	(0.073)	(0.076)	(0.084)	(0.103)
	[0.167]	[0.190]	[0.233]	[0.204]
Indirect link	0.271***	0.248***	0.425***	0.330***
	(0.078)	(0.083)	(0.105)	(0.118)
	[0.169]	[0.198]	[0.222]	[0.211]
Interactions		**Same State**	**Tech. proximity**	**Geo. distance**
Portfolio link×		-0.185	-1.084***	-0.075**
		(0.319)	(0.190)	(0.030)
		[0.658]	[0.336]	[0.041]
Syn. link×		0.483	-0.010	-0.022
		(0.302)	(0.134)	(0.026)
		[0.615]	[0.258]	[0.039]
Indirect link×		0.292	-0.335**	-0.026
		(0.323)	(0.157)	(0.035)
		[0.630]	[0.215]	[0.042]
Observations	124,074	122,586	122,586	122,586
Pseudo-R2	0.051	0.144	0.144	0.208
Prob.> chi2	0.000	0.000	0.000	0.000
Year FE	Yes	Yes	Yes	Yes
Citation Lag FE	Yes	Yes	Yes	Yes
Technology class FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Lead VC Firm FE	Yes	Yes	Yes	Yes

Table 3.6 - Robustness check: excluding Computers and Communications

This tables shows results of estimating weighted logistic regressions. The unit of observation is a pair of patents representing an actual or potential citation (control). The dependent variable is an indicator for whether or not the citing patent actually cited the cited patent. The regression model also uses a constant and a set of fixed-effects as indicated below, but these are not reported to conserve space. Robust standard errors are shown in parentheses, and are double clustered at the cited-company and citing-company level. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Same class	1.225***	1.238***	1.222***	1.230***
	(0.085)	(0.085)	(0.085)	(0.085)
	[0.265]	[0.264]	[0.266]	[0.264]
Same state	0.375***	0.724***	0.380***	0.368***
	(0.050)	(0.090)	(0.050)	(0.049)
	[0.155]	[0.221]	[0.155]	[0.157]
Citation propensity	4.990***	4.936***	5.042***	4.967***
	(1.216)	(1.220)	(1.221)	(1.218)
	[2.367]	[2.369]	[2.345]	[2.354]
Geographic distance	-0.074***	-0.072***	-0.075***	-0.099***
	(0.009)	(0.009)	(0.009)	(0.019)
	[0.020]	[0.020]	[0.021]	[0.049]
Technology proximity	4.851***	4.829***	5.105***	4.847***
	(0.065)	(0.067)	(0.095)	(0.065)
	[0.204]	[0.211]	[0.303]	[0.205]
Portfolio link	0.281***	0.722***	0.805***	0.182*
	(0.079)	(0.114)	(0.092)	(0.097)
	[0.223]	[0.343]	[0.326]	[0.230]
Syndication link	0.185***	0.303***	0.297***	0.152**
	(0.053)	(0.074)	(0.058)	(0.066)
	[0.173]	[0.203]	[0.198]	[0.174]
Indirect link	0.223***	0.343***	0.227***	0.142*
	(0.057)	(0.071)	(0.087)	(0.078)
	[0.178]	[0.206]	[0.224]	[0.208]
Interactions		**Same State**	**Tech. proximity**	**Geo. distance**
Portfolio link×		-0.817***	-0.944***	0.060**
		(0.142)	(0.148)	(0.028)
		[0.375]	[0.409]	[0.057]
Syn. link×		-0.319***	-0.209**	0.016
		(0.106)	(0.099)	(0.021)
		[0.265]	[0.293]	[0.046]
Indirect link×		-0.313**	-0.044	0.038
		(0.125)	(0.133)	(0.025)
		[0.263]	[0.361]	[0.042]
Observations	206,993	205,225	205,225	205,225
Pseudo-R2	0.040	0.235	0.236	0.235
Prob.> chi2	0.000	0.000	0.000	0.000
Year FE	Yes	Yes	Yes	Yes
Citation Lag FE	Yes	Yes	Yes	Yes
Technology class FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Lead VC Firm FE	Yes	Yes	Yes	Yes

Table 3.7 - Robustness check: excluding top VCs

This tables shows results of estimating weighted logistic regressions on the subsample of citations among VC-backed companies not financed by top VCs. Top VCs are those whose investments represent more than 1% of total investments: New Enterprise Associates Inc., Kleiner Perkins Caufield Byers, Oak Investment Partners, U.S. Venture Partners, Mayfield Fund, Accel Partners, Sequoia Capital and Bessemer Venture Partners. The unit of observation is a pair of patents. The dependent variable is an indicator for whether or not the citing patent actually cited the cited patent. The regression model also uses a constant and a set of fixed-effects as indicated below, but these are not reported to conserve space. Robust standard errors are shown in parentheses, and are double clustered at the cited-company and citing-company level. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Same class	1.487***	1.485***	1.469***	1.481***
	(0.113)	(0.114)	(0.112)	(0.113)
	[0.238]	[0.246]	[0.241]	[0.240]
Same state	0.500***	0.698***	0.494***	0.499***
	(0.065)	(0.113)	(0.065)	(0.065)
	[0.173]	[0.339]	[0.172]	[0.168]
Citation propensity	7.888***	7.888***	7.921***	7.930***
	(2.004)	(2.015)	(2.006)	(2.013)
	[3.633]	[3.678]	[3.655]	[3.667]
Geographic distance	-0.067***	-0.067***	-0.068***	-0.069***
	(0.009)	(0.009)	(0.009)	(0.021)
	[0.015]	[0.015]	[0.015]	[0.033]
Technology proximity	4.976***	4.981***	5.285***	4.984***
	(0.088)	(0.091)	(0.123)	(0.088)
	[0.333]	[0.342]	[0.365]	[0.334]
Portfolio link	0.232**	0.450***	0.846***	0.288**
	(0.104)	(0.129)	(0.129)	(0.120)
	[0.267]	[0.324]	[0.342]	[0.282]
Syndication link	0.029	0.243***	0.196***	-0.020
	(0.066)	(0.084)	(0.068)	(0.082)
	[0.220]	[0.201]	[0.232]	[0.257]
Indirect link	0.201***	0.148*	0.265***	0.279***
	(0.061)	(0.080)	(0.078)	(0.086)
	[0.122]	[0.184]	[0.202]	[0.131]
Interactions		**Same State**	**Tech. proximity**	**Geo. Distance**
Portfolio link×		-0.717***	-1.117***	-0.035
		(0.220)	(0.230)	(0.035)
		[0.413]	[0.468]	[0.040]
Syn. link×		-0.468***	-0.360***	0.027
		(0.125)	(0.123)	(0.024)
		[0.380]	[0.244]	[0.041]
Indirect link×		0.240*	-0.147	-0.035
		(0.128)	(0.135)	(0.029)
		[0.250]	[0.278]	[0.036]
Observations	149,000	149,000	149,000	149,000
Pseudo-R2	0.041	0.146	0.149	0.231
Prob> chi2	0.00	0.00	0.00	0.00
Year FE	Yes	Yes	Yes	Yes
Citation Lag FE	Yes	Yes	Yes	Yes
Technology class FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Lead VC Firm FE	Yes	Yes	Yes	Yes

Table 3.8 - Technological convergence in VC networks and turnover of inventors and executives

This table shows results of estimating weighted logistic regressions. The unit of observation is a pair of patents representing an actual or potential citation (control). The dependent variable is an indicator for whether or not the citing patent actually cited the cited patent. The regression model also uses a constant and a set of fixed-effects as indicated below, but these are not reported to conserve space. Robust standard errors are shown in parentheses, and are double clustered at the cited-company and citing-company level. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Same Class	1.555***	1.554***	1.527***	1.522***
	(0.066)	(0.066)	(0.066)	(0.066)
	[0.195]	[0.197]	[0.195]	[0.195]
Same State	0.311***	0.314***	0.320***	0.314***
	(0.037)	(0.038)	(0.036)	(0.036)
	[0.115]	[0.111]	[0.112]	[0.114]
Citation propensity	5.490***	5.475***	5.518***	5.455***
	(1.108)	(1.106)	(1.093)	(1.092)
	[1.792]	[1.809]	[1.787]	[1.793]
Geographical distance	-0.069***	-0.069***	-0.070***	-0.071***
	(0.006)	(0.006)	(0.006)	(0.006)
	[0.013]	[0.013]	[0.013]	[0.013]
Technological closeness	4.575***	4.579***	4.735***	4.746***
	(0.058)	(0.058)	(0.051)	(0.052)
	[0.244]	[0.245]	[0.209]	[0.209]
Inventor Turnover	0.336***	0.602***		
	(0.042)	(0.096)		
			0.003	-0.357***
Executive Turnover			(0.046)	(0.090)
			[0.110]	[0.268]
Portfolio link	0.148***	0.278***	0.229***	-0.131
	(0.055)	(0.065)	(0.064)	(0.101)
	[0.175]	[0.178]	[0.195]	[0.318]
Syndication link	0.154***	0.201***	0.172***	-0.128
	(0.042)	(0.043)	(0.053)	(0.092)
	[0.153]	[0.145]	[0.175]	[0.305]
Incidental link	0.202***	0.217***	0.237***	0.026
	(0.046)	(0.052)	(0.054)	(0.088)
	[0.121]	[0.134]	[0.122]	[0.197]
Interactions		**Inventor Turnover**		**Executive Turnover**
Portfolio link×		-0.417***		0.920***
		(0.113)		(0.144)
		[0.268]		[0.365]
Syndication link×		-0.266**		0.436***
		(0.109)		(0.109)
		[0.368]		[0.287]
Incidental link×		-0.170		-0.050
		(0.121)		(0.129)
		[0.254]		[0.266]
Observations	344,573	344,573	344,573	344,573
Pseudo-R2	0.219	0.219	0.219	0.219
Prob> chi2	0.00	0.00	0.00	0.00
Year FE	Yes	Yes	Yes	Yes
Citation Lag FE	Yes	Yes	Yes	Yes
Technology class FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Lead VC Firm FE	Yes	Yes	Yes	Yes

5 Figures

Figure 2.1 - Estimated temporal trends in citations to patents

The solid lines in the plot correspond to the coefficient estimates of a fixed-effects Poisson model in which the dependent variable corresponds to annual citations to patents, and the explanatory variables are Event Year dummies. I restrict the sample to a [-2,5] year window around the financing event of the issuing company. The 95% confidence interval (corresponding to robust standard errors, clustered at the issuing company level) around these estimates is plotted with dashed lines. The reference period for interpreting the plot is the year of the VC investment (Event Year 0).

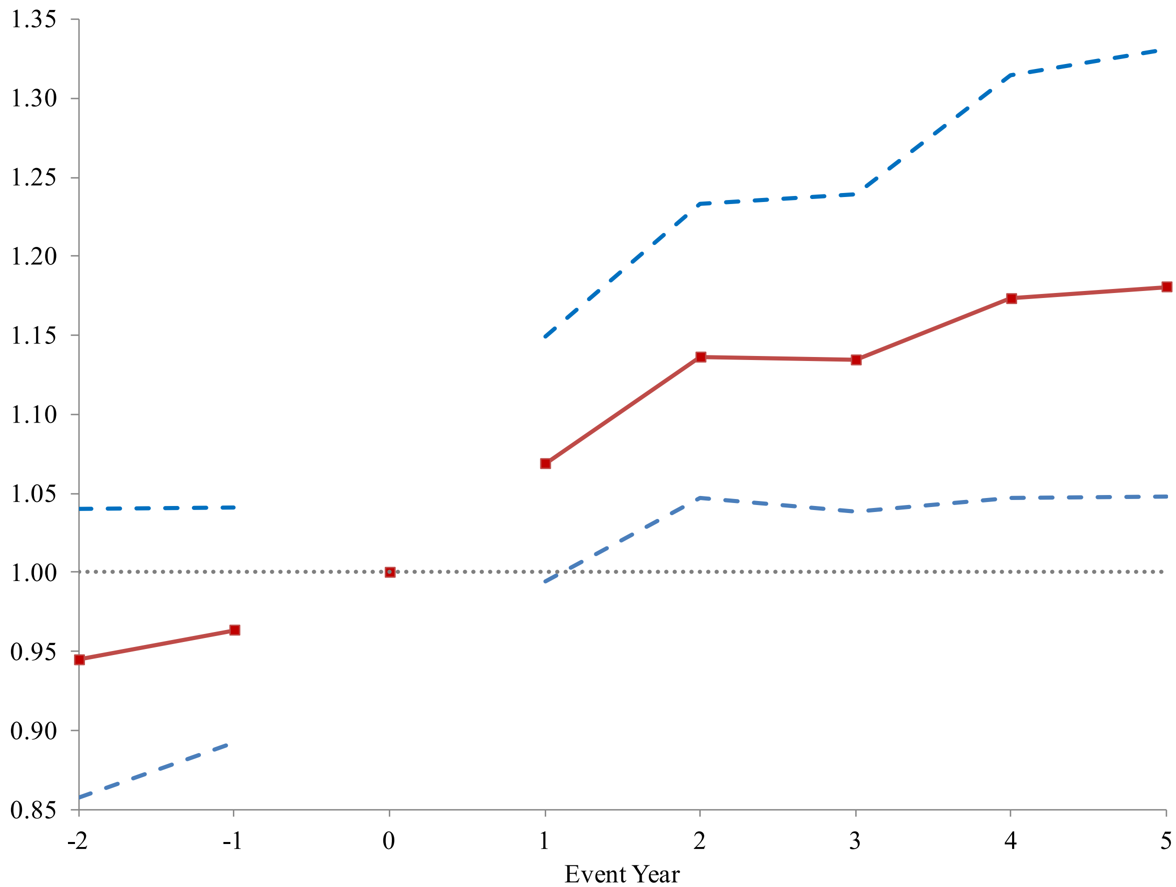


Figure 2.2 - Patent sale likelihood

The figure presents the annual probability that a patent is sold in the two years before, and nine years after a VC invests in the issuing company. The solid line describes patents in my sample, and the dashed line corresponds to matching patents at the technology-class and application- year, and that were not financed by a VC.

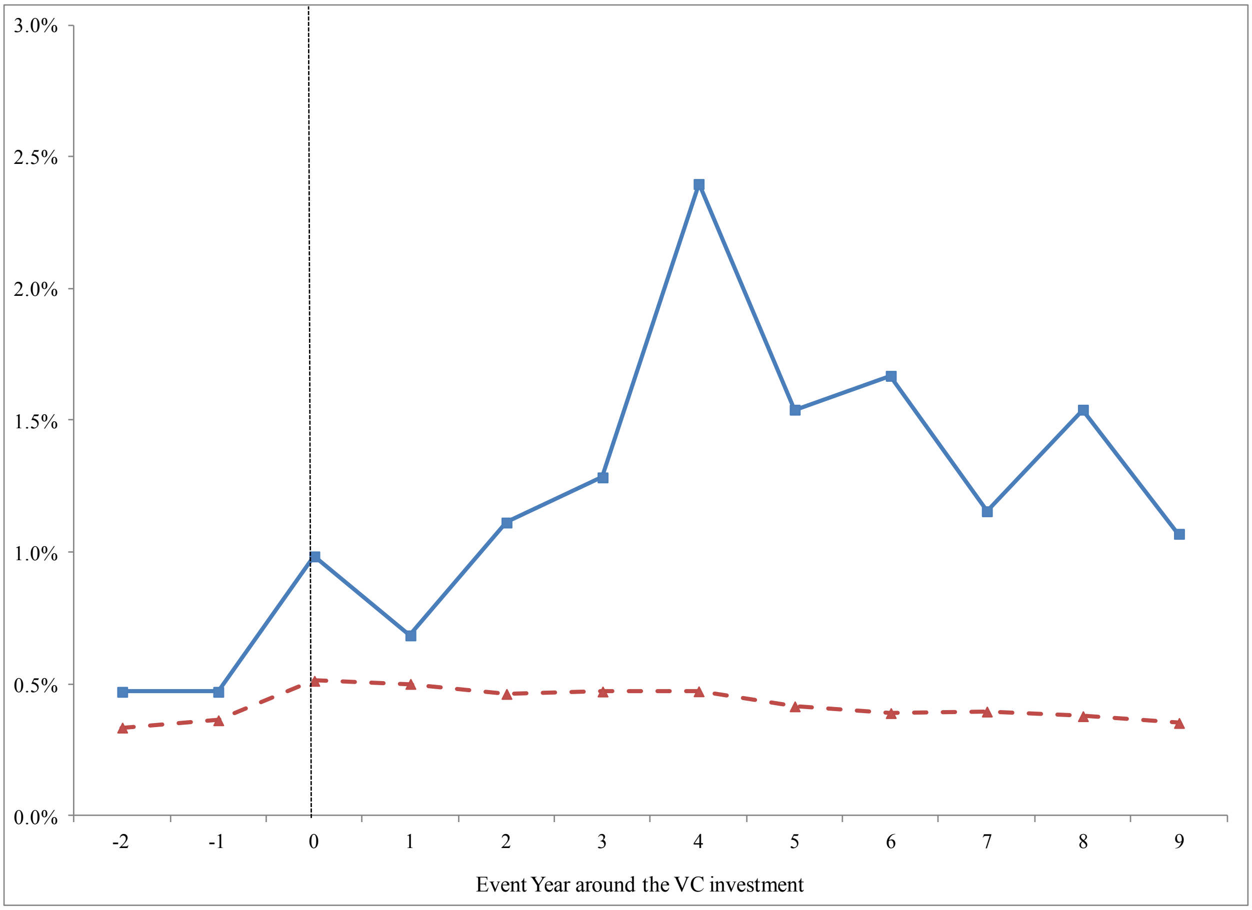


Figure 2.3 - Exposure Effect of VC investments

The figure presents the normalized annual searches made in Google to companies that were first financed by a VC in 2006. To construct the graph, I strip company names of punctuation, capitalization and common acronyms and search for weekly hits in Google Insights since January 2004 until the end of 2011. The solid line corresponds to average annual searches to the normalized names, relative to the total number of searches done on Google over time. The dashed lines correspond to average annual searched to the word "Gold". Google Insights analyzes only a portion of Google web searches to compute how many searches have been done for the entered terms, relative to the total number of searches done on Google over time. This analysis indicates the likelihood of a random user to search for a particular search term at a certain time. Google Insights designates a certain threshold of traffic for search terms, so that those with low volume won't appear. It also eliminates repeated queries from a single user over a short period of time, so that the level of interest isn't artificially impacted by this type of queries. The information on companies that were first financed by a VC in 2006 is from SDC Thompson.

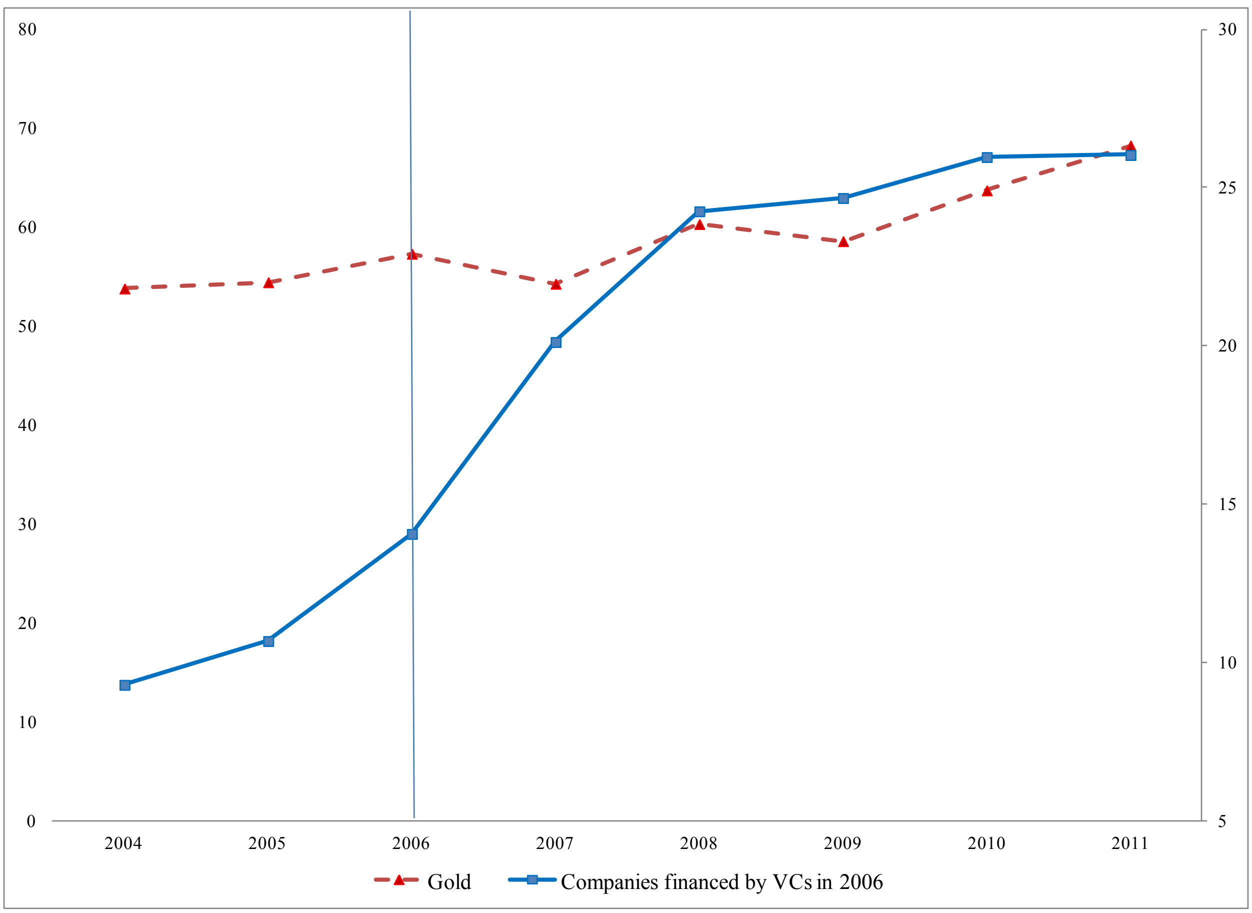


Figure 3.1 - Illustration of VC-proximity links

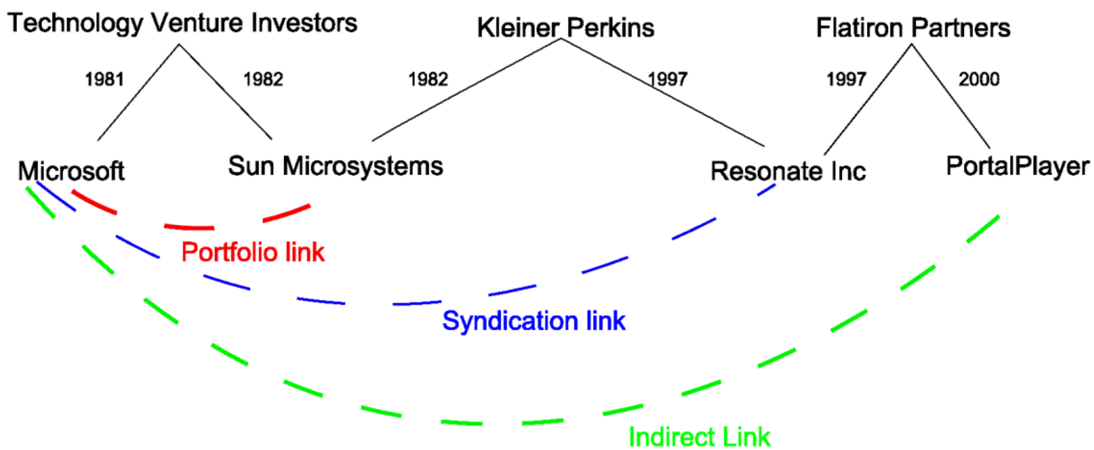
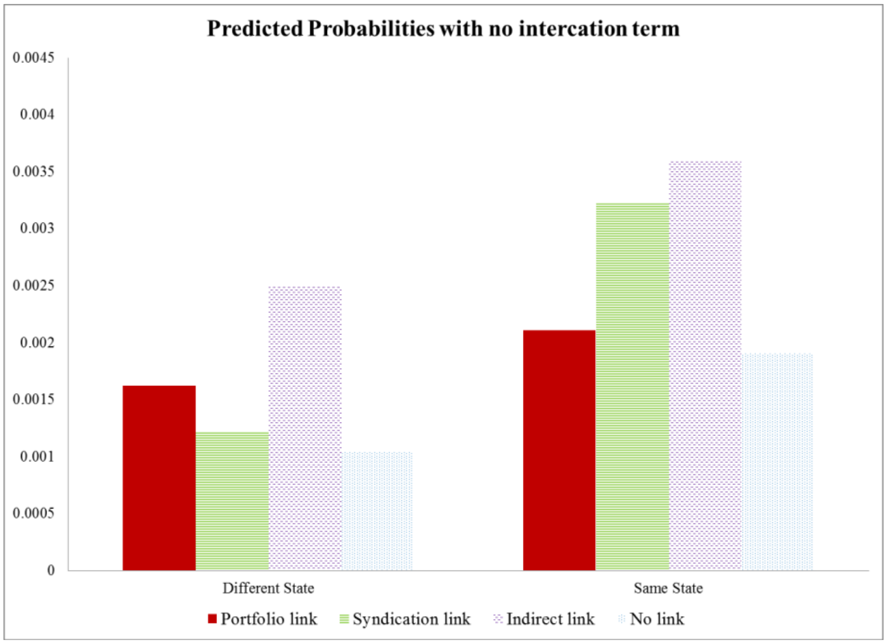


Figure 3.2 - Predicted probabilities across geographical distance and VC-proximity

This figures plot predicted probabilities. The left panel plots the predicted probabilities of a citation for the different types of VC-proximity links using the basic model with no interaction terms. The right panel plots the predicted probabilities using the model that includes the second order terms of the interactions. The "interaction effect" is interpreted as the distance between the sets of predicted probabilities among the different types of VC-inferred links.



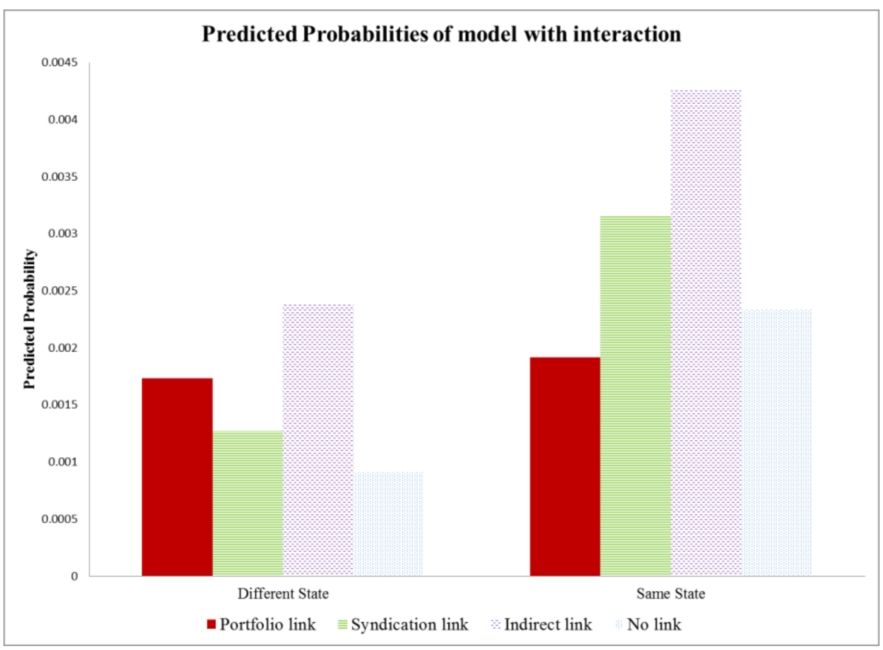
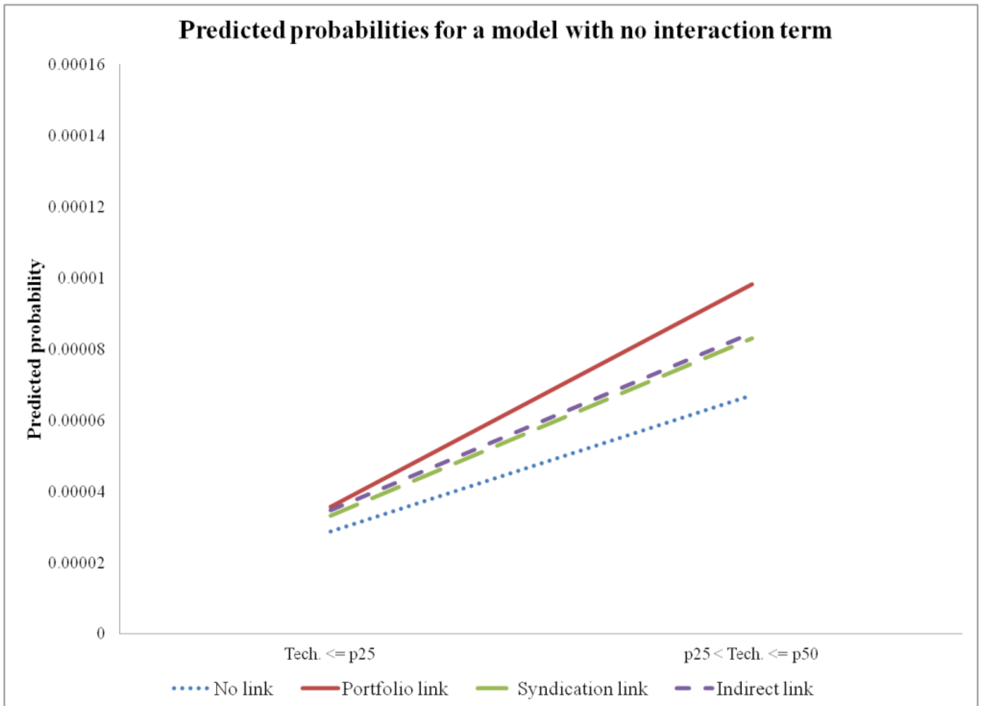
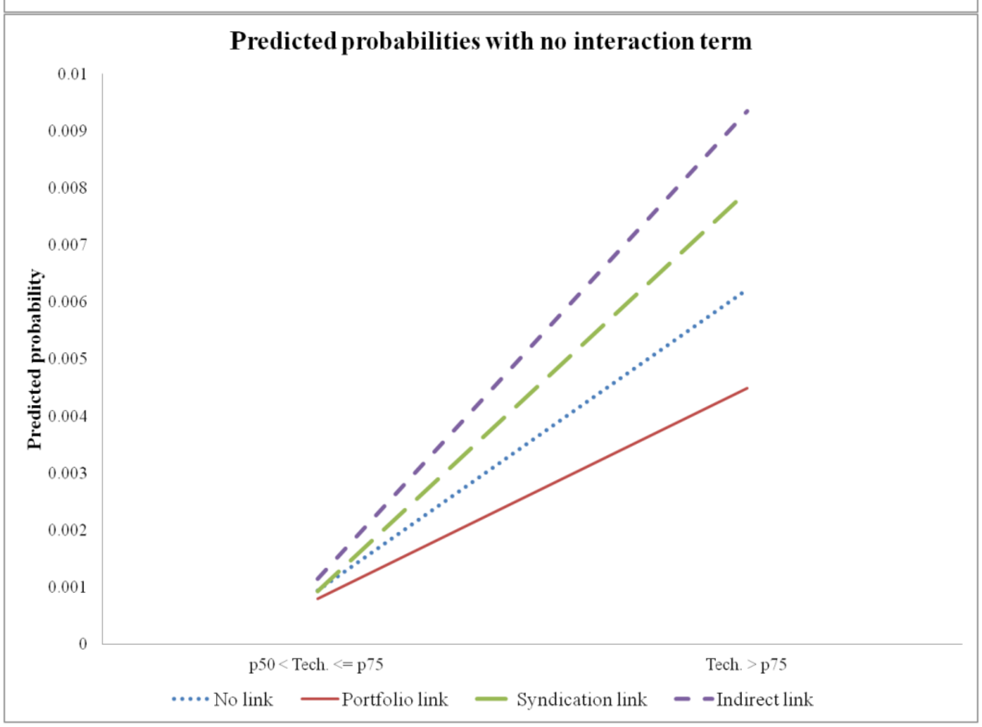


Figure 3.3 - Predicted probabilities across technological-proximity and VC-proximity

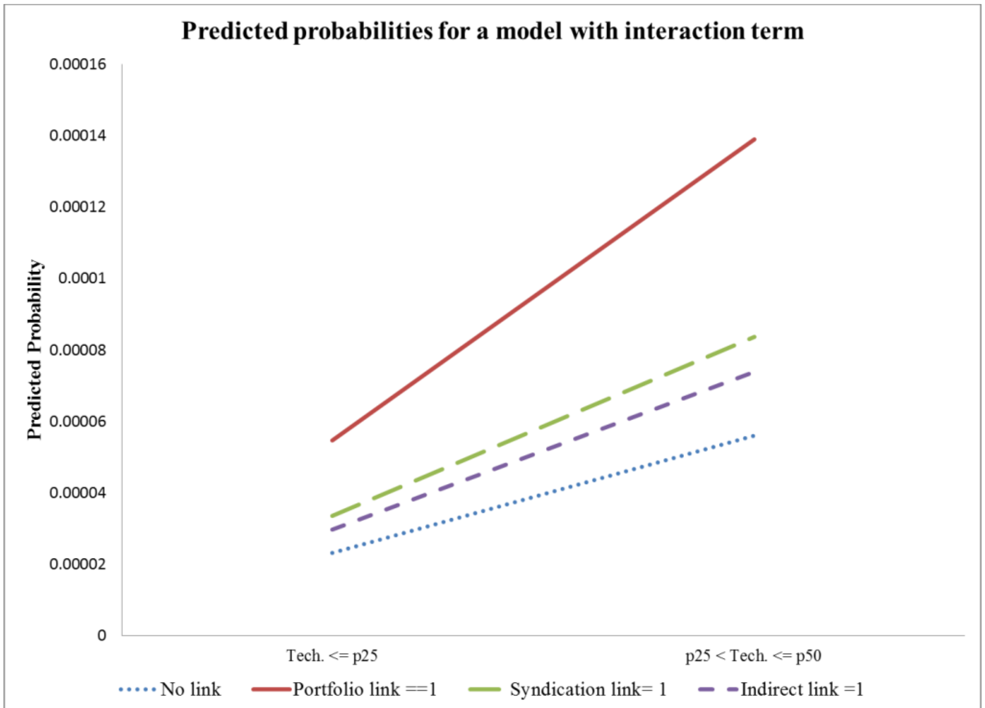
These figures plot predicted probabilities. The first panel plots the average predicted probabilities for the different types of VC-proximity links using the basic model with no interaction terms. The second panel plots the predicted probabilities for the expanded model that includes interactions between the types of VC-proximity links and the technological proximity of companies. The figures to the left (for both panels) present the predicted effects of a transition from a 25th to a 50th percentile in technological proximity between filing companies. The figures to the right (for both panels) present the predicted effects of a transition from a 50th to the 75th percentile in technological proximity between filing companies.

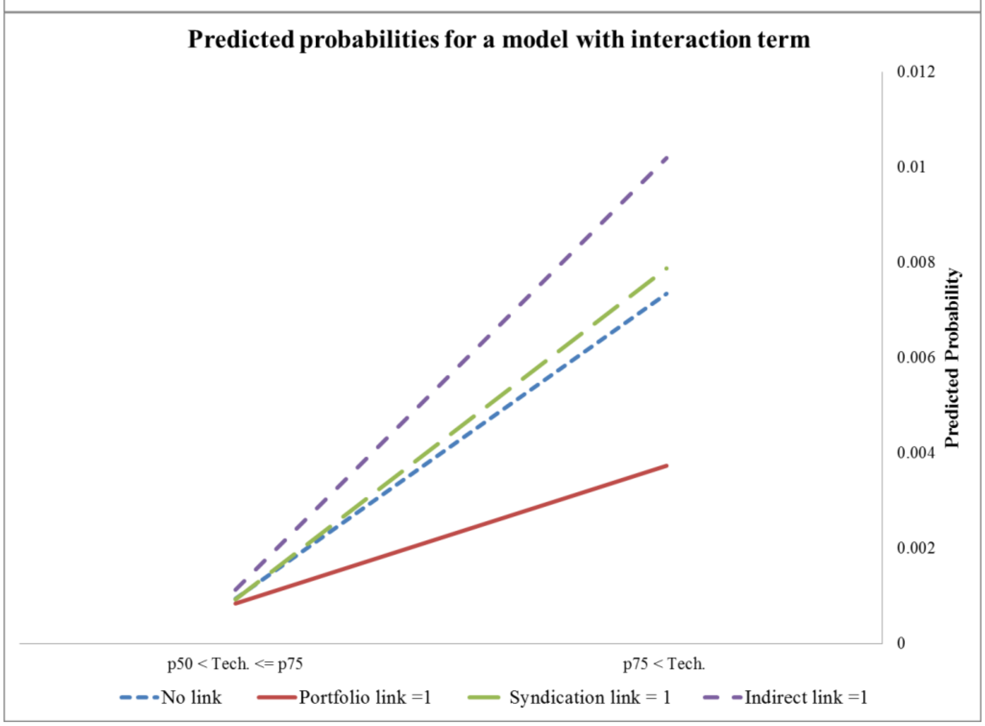
Panel A





Panel B


Predicted probabilities for a model with interaction term
0.00016
0.00014
0.00012
0.0001
0.00008
0.00006
0.00004
0.00002
0
Predicted Probability
Tech. <= p25
p25 < Tech. <= p50
No link
Portfolio link ==1
Syndication link= 1
Indirect link =1


Predicted probabilities for a model with interaction term
0.012
0.01
0.008
0.006
0.004
0.002
0
Predicted Probability
p50 < Tech. <= p75
p75 < Tech.
No link
Portfolio link =1
Syndication link = 1
Indirect link =1

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7 Appendix: Construction of Dataset

My starting point is the universe of transactions registered in VentureXpert that closed between January 1976 and December 2009. I eliminate four types of investments. First, VentureXpert contains transactions by private equity groups other than independent Venture Capital firm such as angel groups, bank affiliate firms corporate venture capital firms endowment foundations, pension funds, government affiliate programs, incubator development programs, individuals, insurance fir affiliate and investment management firms While these transactions are part of the financia landscape for companies, they are not the focus of this study; hence, I eliminate them from the sample. Second, the data contain transactions by VC firm that are not focused on venture capital, such as buyout funds and funds of funds, and I eliminate these deals as well. I also remove investments by VC firm in companies that were already traded in public markets before the transaction (called PIPEs), and secondary purchases. Finally, I only include investments made by U.S. VC firm in U.S. companies. After these eliminations, the data contain 116,574 investments made to 20,058 U.S. based companies. After these eliminations, the data contain 116,574 investments made to 20,058 U.S. based companies.

7.1 Capturing patent data

I match the companies involved in VC transactions to their patent records based on name. To do so, I employ the Harvard Business School (HBS) patent database. The HBS data contain all electronic records of the U.S. Patent and Trademark Offic (USPTO) through December 2008, which have been cleaned and consolidated by HBS.[1] The patent database also has information on all citations made and received by patents as well as information on the inventors. I restrict my sample to primary assignments of utility patents (99%) awarded to US companies from 1976

[1] The database is documented in Lai, D'Amour, and Fleming (2009).

onwards. After these restrictions the sample consists of 2,881,097 patents, awarded to 1,980,696 inventors, and issued to 242,767 U.S. assignees.[2] The total number of citations made and received by these patents is 22,511,338.

In order to combine the two databases, I strip company names from VentureXpert, and assignee names from the HBS database, of punctuation, capitalization and common acronyms. I then match the samples on the normalized company and assignee names using a fuzzy-match procedure based on the Levenshtein edit distance. The Levenshtein edit distance is a measure of the degree of proximity between two strings, and corresponds to the number of substitutions, deletions or insertions needed to transform one string into the other one (and vice versa).[3] I assign a score for each match as a function of the Levenshtein edit distance and the length of each of the normalized company names in the match. Using a random sampling procedure, I determine a score threshold such that matches with scores above the threshold are hand checked, and those below the threshold are eliminated. During the manual check of the remaining matches, I check that the two companies are in the same state. There are ambiguous situations where the names are similar, but not exactly identical, or where the location of the patentee differs from that given in the records of SDC. In these cases, I research the potential matches using web searches. Finally, in some cases, there are multiple names in either of the bases that appear to match a single name in the other data set. For these, I add the observations into an aggregated entity.

7.2 Sample

In total, I identify 5,018 companies that are VC-backed and with at least one U.S. utility patent grant. The total number of patents awarded to these companies from January 1976 to December

[2]The assignee of a patent is the individual or entity that owns the patent.

[3]For more information and an application to Perl see Text::LevenshteinXS in CPAN.

2008 is 105,484 patents. The total number of inventors in the sample is 74,666 inventors, and the total number citations made and received by these patents is 1,200,190. The total number of VC firm that invest in these companies is 1,383 with 41,401 investments in the companies.

The small number of matches between the two data sets likely reflect two facts. First, in many instances, specially more recently, the companies that are VC-backed belong to sectors in which IP is not usually protected using patents (e.g. internet, media, and software companies), and in which there is greater reliance on trade secrets to protect it. Second, VentureXpert includes data on all companies that received VC financing including those that were not ultimately successful, and which may not have reached a stage in which IP should be protected.

Note that the 105,484 patents assigned to VC-backed companies correspond to less that 4% of U.S. patent stock. This stands to contrast with existing estimates from the venture capital literature on the patent stock of patents attributed to venture capital funds. For example, Kortum and Lerner (2000) analyze annual data from twenty manufacturing industries. The dependent variables is U.S. patents issued to U.S. inventors by industry and date of application. The main explanatory variables are measures of venture funding collected by Venture Economics. The authors estimate a patent production function and estimate the impact on patenting that a dollar of venture capital has relative to a dollar of R.&D on industrial patent production. Using a back-of-the-envelope calculation of their findings the author estimate that venture capital funds have accounted for approximately 14% of industrial patent production. More recent studies by Hirukawa and Ueda (2011) confir the order of magnitude of this estimate. The difference between these macro-based estimates, and my micro-based quantification suggests that VCs generate knowledge spillovers, and that their role on innovation goes above and beyond financin the patents of their targets.

Before I discuss summary statistics of the matched sample, a couple of points need to be clarifie regarding institutional arrangement of patent data. There are two relevant dates associated with each patent: application and grant date. The application date marks the officia date in which the inventor submitted the patent application to the USPTO office The grant date is the date in which the patent was issued to the inventor. For patents applied for before October 2000, their content was made public the firs Tuesday after grant date in the USPTO's officia magazine. For patents applied for after October 2000, the American Inventor Protection Act (enacted on November 29 1999) specifie they are to be disclosed 18 months after application. Nevertheless, citations to patents start as early as the application year, which can be partially explained by technical disclosures, or diffusion of new technologies via conferences or connections among agents.

7.3 Summary Statistics

Table A.1 presents summary statistics of the matched sample. Panel A shows an apparent decrease in patent applications by VC-backed companies starting on 2002. The reason for this decrease is the well documented lag between the application and the grant of a patent by the USPTO office

For patents issued after 1976 and granted to any (VC-backed) patentee by 2008, the lag is 2.30 (2.75) years. The difference in the lag between Non VC- and VC-backed assignees is not significant Panel A also shows an apparent decrease in the number of investments by VC-backed companies. This decrease is due in part to the expansion of investments in sectors such as internet and media that do not generally rely on patent protection, and not to a real decrease in the number of total investments by VCs. Panel B exhibits the distribution of patents and VC-backed companies that patent by state. As it is common in the VC literature, the sample is concentrated in California, Massachusetts, Washington and Texas. Panel C shows the distribution of type of firs time investments by VC firm on companies that patent. The types of investments include traditional VC investments such as: Bridge Loans, Early Stage, Expansion, Later Stage and Seed. Panel D shows the distribution of companies that patent by industry, according to the industry classificatio from SDC. The data is concentrated in Medical Health, Semiconductors and Computer Software. Panel E shows distribution of VC-backed companies that patent by type of VC exit. Approximately

50% of companies have a successful exit, either through an IPO or acquisition. Finally, Panel F lists the companies that have a disproportionate share of patents in my sample (more than 1% of the sample). This group of companies includes well known successful examples of VC-backed investments such as Sun Microsystems, Intel and Microsoft.

Table A.2 compares patents from VC-backed companies and patents issued to Non VC-backed assignees. Panel A shows that patents assigned to VC-backed companies receive more citations three years following the grant date. This is true for both citations made by the same assignee (self-citations) and citations made by other assignees (no self citations).

The generality measure is an statistic used in the innovation literature to describe patents, and is constructed using information on the citations received by patents. A patent has a higher generality, if it is cited by subsequent patents that belong to a wide range of technology classes. Thus, a high generality score suggests the patent presumably had a widespread impact, in that it influence subsequent innovations in a variety of fields The generality measure corresponds to one minus the Herfindah index of the technology classes of the citing patents. Panel B, shows that patents assigned to VC-backed companies have higher generality measures three years following the grant date.

The originality measure is an additional statistic used in the innovation literature to describe patents, and is constructed using information on the citations made by patents. A patent has a higher originality, if it cites patents that belong to a wide range of technology classes. The intuition is that patents that combine existing knowledge from few technology classes to create something new (and useful), probably constitute more marginal improvements relative to patents that combine more ex-ante different ideas. This measure is constructed as one minus the Herfindah index of the cited patents across technological classifications Panel C shows that VC-backed patents are on average more original.

8 Tables Appendix

Table A1 - Summary statistics of matched sample

The matched full sample consists of 105,484 patents awarded between 1976 and December 2008 to 5,018 companies that were financed by at least one U.S. VC firm during 1976 to 2009.

Panel A. Application and grant years of patents issued by VC-backed companies and total number of VC-backed companies by year of first VC transaction

	Patents		Companies	
	Applications	Grants	Number	Percentage
1976	247	3	20	0.4
1977	243	113	24	0.48
1978	258	225	29	0.58
1979	260	182	37	0.74
1980	246	232	77	1.53
1981	340	229	139	2.77
1982	348	217	113	2.25
1983	421	251	123	2.45
1984	518	369	138	2.75
1985	570	397	111	2.21
1986	696	463	103	2.05
1987	860	671	122	2.43
1988	1,007	699	112	2.23
1989	1,162	1,009	147	2.93
1990	1,321	976	100	1.99
1991	1,581	1,057	60	1.2
1992	1,939	1,325	77	1.53
1993	2,309	1,562	91	1.81
1994	3,166	1,814	95	1.89
1995	5,130	2,104	175	3.49
1996	5,405	2,689	214	4.26
1997	7,000	3,287	247	4.92
1998	7,354	5,288	295	5.88
1999	8,208	5,767	333	6.64
2000	9,825	6,433	497	9.9
2001	10,537	6,891	308	6.14
2002	10,583	7,424	245	4.88
2003	8,133	8,236	242	4.82
2004	7,379	7,961	236	4.7
2005	5,338	7,498	180	3.59
2006	2,430	10,139	134	2.67
2007	643	9,906	102	2.03
2008	27	10,067	67	1.34
2009			25	0.5
Total	105,484	105,484	5,018	

Panel B. Distribution of Patents and VC-backed companies by state

	Patents		Companies	
	Number	Percentage	Number	Percentage
AL	309	0.29	10	0.2
AR	1	0	1	0.02
AZ	562	0.53	47	0.94
CA	59,644	56.54	2,226	44.36
CO	1,275	1.21	137	2.73
CT	796	0.75	84	1.67
DC	72	0.07	8	0.16
DE	36	0.03	2	0.04
FL	674	0.64	75	1.49
GA	469	0.44	88	1.75
HI	6	0.01	2	0.04
IA	25	0.02	9	0.18
ID	58	0.05	7	0.14
IL	671	0.64	97	1.93
IN	332	0.31	15	0.3
KS	14	0.01	8	0.16
KY	11	0.01	4	0.08
LA	29	0.03	6	0.12
MA	9,469	8.98	643	12.81
MD	939	0.89	106	2.11
ME	13	0.01	3	0.06
MI	303	0.29	43	0.86
MN	2,713	2.57	91	1.81
MO	157	0.15	23	0.46
MS	16	0.02	5	0.1
MT	5	0	1	0.02
NC	882	0.84	80	1.59
ND	6	0.01	1	0.02
NE	20	0.02	3	0.06
NH	492	0.47	49	0.98
NJ	1,198	1.14	129	2.57
NM	52	0.05	14	0.28
NV	67	0.06	9	0.18
NY	1,905	1.81	146	2.91
OH	538	0.51	62	1.24
OK	63	0.06	10	0.2
OR	523	0.5	55	1.1
PA	2,370	2.25	155	3.09
RI	54	0.05	12	0.24
SC	19	0.02	6	0.12
SD	4	0	1	0.02
TN	164	0.16	21	0.42
TX	6,206	5.88	243	4.84
UT	204	0.19	33	0.66
VA	483	0.46	69	1.38
VT	26	0.02	3	0.06
WA	11,242	10.66	144	2.87
WI	359	0.34	28	0.56
WV	2	0	2	0.04
WY	6	0.01	2	0.04
Total	105,484		5,018	

Panel C. Distribution of type of investment by VC firms in companies that patent

Type of Investment	Number of deals	Percentage of sample
Bridge Loan	85	1.69
Early Stage	1,917	38.2
Expansion	1,269	25.29
Later Stage	350	6.97
Seed	1,397	27.84
Total	5,018	

Panel D. Industry distribution of VC investments in companies that patent

	Number of companies	Percentage of sample
Biotechnology	495	9.86
Communications and Media	554	11.04
Computer Hardware	446	8.89
Computer Software	819	16.32
Consumer Related	101	2.01
Industrial Energy	400	7.97
Internet Specific	425	8.47
Medical Health	842	16.78
Other Products	131	2.61
Semiconductors	805	16.04
Total	5,018	

Panel E. Distribution of VC-backed companies with prior patents by type of VC exit

	Number of companies	Percentage of sample
Acquisition	1,722	34.32
Active	1,537	30.63
Bankruptcy - Chapter 11	23	0.46
Bankruptcy - Chapter 7	38	0.76
Defunct	726	14.47
In Registration	20	0.4
LBO	37	0.74
Merger	82	1.63
Other	20	0.4
Pending Acquisition	7	0.14
Went Public	806	16.06
Total	5,018	

Table A2 – Comparison Patents from VC-backed versus Non VC-backed patents

The full matched sample consists of 105,484 patents awarded through December 2008 to 5,018 companies that received VC backing between 1976 and 2009Panel B, presents citation counts 3 years following the grant date, and excludes from the analysis patents granted after 2005. Panel C, presents Generality measures using the USPTO technological classification and the Hall bias correction (Hall, et al. 2001). Panel D, presents Generality measures for citations 3 years following the grant date. Panel E, presents Originality measures. See Appendix 1 for a detailed definition of the variables.

Panel A. Total Citations, Self-citations and No-self citations until 3 years after grant date

	Three-year Citations			Three-year Self Citations			Three-year No Self Citations			
	Mean	S.D.	Med.	Mean	S.D.	Med.	Mean	S.D.	Med.	Obs.
VC-backed	7.4	13.79	3	1.23	4.15	0	6.17	12.22	2	95,110
Non VC-backed	3.32	6.56	1	0.53	1.91	0	2.79	5.95	1	2,652,052
p-value t-test	0.00			0.00			0.00			

Panel B. Generality, Self Generality and No-self generality until 3 years after grant date

	Three-year Generality				Three-year No Self Generality			
	Mean	S.D.	Med.	Obs.	Mean	S.D.	Med.	Obs.
VC-backed	0.40	0.28	0.48	64,946	0.39	0.29	0.47	61,648
Non VC-backed	0.28	0.28	0.28	1,734,688	0.26	0.28	0.17	1,605,061
p-value t-test	0.00				0.00			

Panel C. Originality

	Originality				Originality Adjusted			
	Mean	S. D.	Med.	Obs.	Mean	S. D.	Med.	Obs.
VC-backed	0.455	0.283	0.5	105,484	0.56	0.31	0.50	99,551
Non VC-backed	0.305	0.293	0.32	2,775,613	0.436	0.37	0.32	2,451,091
p-value t-test	0.00				0.00			