Banks as "anchors": the role of banks in funding innovation*

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Abstract

Bank investments in the venture capital (VC) market play an important role, especially outside main entrepreneurial hubs. Banks act as anchors to the companies, serving as a positive signal of their quality and attracting further investors. Due to their abilities in monitoring and higher local expertise, banks are able to select profitable VC investments and exit them successfully. I exploit the implementation of the Volcker Rule as a shock where banks are no longer allowed to sponsor or invest in VC funds. I find that companies in regions dependent on bank VC financing suffer a drop in financing and innovation. A proxy for attention to start-ups serves as another confirmation mechanism of our story. I add to the debate on cross-selling services by financial intermediaries and on the certification role that banks play in markets other than lending.

Keywords: entrepreneurship, venture capital, banking, innovation, early-stage financing, Volcker Rule

JEL Codes: G21, G24, O30

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1 Introduction

Venture capital investments are generally seen as key innovation drivers for the US economy and they are known to account for half of the total number of listings and 92% of the R&D spending of public companies in the last 50 years (Gornall & Strebulaev, 2020). After the financial crisis, however, the excitement for venture capital investments has also been met by political backlash. Considered an overreach of regulation following the crisis, the Volcker Rule prohibited banks from sponsoring or directly investing in covered funds, comprising private equity investments and hedge funds. This paper focuses on the lower size of the private equity spectrum, respectively on the restriction of bank's investments into the venture capital market. For instance, a National Venture Capital Association letter to the five main federal financial agencies underlines precisely the harmful consequences of restricting bank investments in the venture capital market.[1] This addresses the disconnect between the main objective of the regulation, which is decreasing the systemic risk in the banking sector, against the harmful consequences of the regulation on new company formation and growth. Another key point of the letter was underlining the inadvertent harmful geographic effects of regulation. Outside the well-established main entrepreneurial hubs, such as California, New York and Massachusetts, venture capital firms benefit from the valuable role of banks as "anchor investors". In these areas with emerging entrepreneurial ecosystems, banks play a stabilizing role, both through an increased financial security that they offer to the companies, through a certification role that they play based on their expertise in small business financing and through the potential future cross-selling opportunities which they can offer to these firms.

Bank investments in the VC market have risen to prominence in the 1980s and early 2000s but have regained increased attention following the financial crisis and the implementation of the Volcker Rule. According to financial data provider Preqin, banks represented 8% of the aggregate capital invested in the private equity market in 2011. From the banks surveyed in their study, a quarter were planning to increase the capital amounts committed in the coming years. However, the main challenge they were facing was the impact of regulatory changes on their ability to deploy capital into the asset class and the long-term consequences this would have for their investing strategy.[2]

What is striking about this debate is the paucity of information to address it. Common

[1] National Venture Capital Association Letter

[2] As retrieved from Preqin

understanding about the venture capital activities of funds outside large hubs cannot explain the effect of bank financing on the average start-up, much less the effect it has on innovation. Even representative statistics about the industry supplied by commercial providers fail to identify the causal relationship between bank VC investments and start-up outcomes. Among possible issues that impede causal identification, self-selection into VC syndicates might be attributed to individual companies which makes treated and non-treated companies difficult to distinguish. Banks also choose some specific regions in which to operate while independent VC might not be present there.

In this paper I investigate the role that bank VC investments play in funding innovation in the United States. In particular, I examine whether banks are a special type of VC investor (Andrieu & Groh, 2012) through the anchoring role that they play vis-a-vis the start-ups they fund and whether they are particularly skilled investors as measured by companies' success. I further compare the difference between bank investments in the US Midwest region and the rest of the country and exploit the variation at the state-level in the dependence on banks as VC investors around the implementation of the Volcker Rule. Finally, I collect a novel data sample of attention paid to start-ups companies before their first VC round and I use it as an instrument in predicting the amount of innovation and the effect it has in regions strongly affected by the legislation.

I first ask what makes bank-affiliated VC funds special investors in the market. I examine the different types of investments that happen in the Midwest region of the United State and I compare it with non-Midwest states. A key reason to do this comparison is because the Midwest is generally more dependent on bank financing in the VC market which makes the effect of the Volcker Rule relatively stronger for companies located there. I find that VC investments are made in Midwest less often during peaks of the PE market, the companies are generally smaller and they raise their first financing round at a higher age. These investments seem to be generally less successful as measured by their acquisition or IPO rates. I then focus on how bank investments compare to independent private equity firms in making venture capital investments. A key result here is that banks tend to invest large amounts in individual rounds regardless of whether the investment takes place in the Midwest or not. Furthermore, this large investment in specific rounds stays constant although companies raise a much smaller amount of capital in the Midwest. This is in contrast with independent PE firms which generally invest less in smaller markets. Bank investments are also part of larger syndicates, provide capital for companies which eventually raise more funding (relative to independent VCs) and they are in aggregate more successful as measured by the IPO/acquisition outcomes. Adding depth to the previous result, bank investments do tend to be higher in Midwest during peaks of the PE market and also during recession periods relative to independent VCs.

A second dimension of my analysis focuses on the ability of bank venture capital investors to pick successful companies. For this, I examine in a cross-section of company outcomes the predictive power of having a bank as a VC investor on the success rate, revenue, employment and innovation activity. First, in a specification where I include all available types of VC investors according to the classification in VentureExpert and a battery of controls, I find that banks have the strongest predictive power on success among all investors. Interesting results appear for government-affiliated funds which have a negative prediction power on success and incubator VCs which have a negatively predictive power on innovation. A second specification uses richer company level controls in order to take out additional variation at the company level and still leaves predictive power to our interest coefficient, which translates to a 50% increase in the probability of success relative to the unconditional mean when having a bank as a VC investor. I also confirm a result from previous literature that bank investments during peaks of the market are less likely to be successful (Fang, Ivashina, & Lerner, 2013). I then empirically test whether banks play an anchoring role for individual companies. I construct a panel of company-round financing events and I look whether having a bank investor in a given round leads to a larger amount being raised in the following rounds or to a larger number of investors taking part in the next round syndicate. I use a more formal propensity score matching approach where I compare similar companies, at the same point in their VC lifetime, where one receives a bank VC investment during a round while the other does not. I find that the average effect of receiving a bank VC round is a $2 million larger future round and 0.5 more investors relative to a company without bank investments.

Third, I construct a proxy for state entrepreneurial growth financing by bank VCs by looking at the average historical growth rate in the number of bank VC investments. I compute a ranking of bank VC growth where more established entrepreneurial states such as California, New York or Massachusetts have seen a lower growth relative to up-and-coming hubs such as Kansas, Missouri or Utah. The higher likelihood of these states to be strongly impacted by the introduction of the Volcker Rule generates heterogeneity in evaluating the impact of the regulation at the state level. I analyse the effect of the regulation at the state-year, fundraising-year and company level and I find a significant drop both in terms of the number and volume of funds raised. I find the drop to be driven mostly by a decrease in fundraising of smaller funds. At the company level I find an immediate drop in the size of the first rounds raised following the Volcker Rule in states highly dependant on bank VC financing and a delayed negative effect on the innovation produced by these firms. These effects are robust to the inclusion of Californian firms or to the choice of time-window.

Finally, I turn more broadly to the innovation activity taking place post Volcker Rule in the entrepreneurial Midwest. A discontinuous drop in innovation appears to take place post 2014 in states which are strongly impacted by the change in regulation. I test this link between bank investments and innovation by collecting a novel set of data on attention paid to all venture companies as measured by GoogleTrends searches. I use this as an instrument for estimating the size of the firm's first venture capital round. I exploit this variation in predicting future innovation at the firm level, effect which is significant overall, in non-Midwest companies but is not significant in the post period for companies located in states highly affected by the Volcker Rule.

Overall, this paper is arguing that banks play an important role in the VC market, both through "anchoring" future investment rounds and value-added activities, but also through a decrease in financing risk of innovation. I show that negative externalities on innovation arise when banks are not allowed to act as players in the VC market, especially in growing entrepreneurial regions, where physical location and expertise of banks is extremely important.

The next section introduces papers in the related literature. Section 3 describes the data used and institutional details about the market. Section 4 presents descriptive statistics on the role of banks as investors Midwest. Section 5 describes the role of banks as anchor investors for a company. Section 6 analyses the effect of the Volcker Rule shock for states highly dependant on bank financing. Section 7 introduces the instrumental variable approach on innovation. The final section concludes.

2 Related literature

There is a rich body of literature showing how venture capital has been a key source of financing for breakthrough innovations in the United States as underlined in Kortum and Lerner (2000); Samila and Sorenson (2011); Lerner and Nanda (2020). Most of the innovation that arose through the emergence of new industries (biotech, semiconductors, internet) was made possible by the financing provided to innovative start-ups through the VC market. Papers such as Chemmanur, Krishnan, and Nandy (2011) and Puri and Zarutskie (2012) follow US companies from their inception using the Longitudinal Research Database of the US Census Bureau and prove that VC firms increase the overall efficiency of the start-ups they invest in. They show that improvement comes from high screening and sustained monitoring and that most of the growth in efficiency takes place during the first two financing rounds. They also show that high-reputation VCs have stronger monitoring abilities and positively affect the probability of a successful exit, thus they strengthen the positive view on the effect of VC firms providing financing to young firms.

Closer to our focus, looking at the incentives of banks to invest in the VC market, older papers investigate cross-selling opportunities that arise for financial holding companies when building relationships early with young firms. Petersen and Rajan (1994) and Berger and Udell (1995) show that it is beneficial for small firms to maintain strong relationships with their bank in order to obtain better credit access and lower fees on their financing. Other papers are looking at concurrent lending and underwriting and due to a certification role that the bank plays, there exists a strong relationship between the lending services that the bank provides and the cross-selling of additional services, such as advising or underwriting, which brings benefits both for the companies (through lower fees) and for the banks (through additional business opportunities) (Yasuda, 2005; Drucker & Puri, 2005). Furthermore, the work of Hellmann, Lindsey, and Puri (2008), Metrick and Yasuda (2011) and Fang et al. (2013) which examines the investments of bank-affiliated venture capital firms into the private equity market builds an extremely important bridge to our discussion. The linking piece of these papers is the bank's incentive in cross-selling additional financial services, which becomes higher during booms of the credit market (when the bank is able to provide cheaper credit, not necessarily more successful for the firm) and focused on financing provided for the larger segment of the market, leveraged buyout (LBO) transactions. The benefit for a PE sponsor in interacting repeatedly with a bank is the fact that it manages to obtain better pricing terms and more favourable covenant requirements every time. Moreover, the initial pricing of the loan is done in order to obtain additional further business from the PE firm. A theoretical connection here is built in a model which makes the distinction between independent PE firms and bank-affiliated (or captive) firms as proposed by Andrieu and Groh (2012). They compare the choice of an entrepreneur between an independent bank venture capitalist and a bank-affiliated venture capitalist depending on the sophistication of its project and on its financing needs. Bank-affiliated investors in this model are seen as deep-pocketed investors able to provide refinancing while independent VCs are better at monitoring and value-adding activities. The insight of the model is that entrepreneurs with less sophisticated ventures and larger liquidation values should choose bank-affiliated investors while entrepreneurs in need of guidance with more uncertain projects should self-select towards an independent VC.

Another area to which our paper is aiming to contribute is venture capital-sponsored innovation. Recent papers such as Lerner and Nanda (2020); Howell, Lerner, Nanda, and Townsend (2021) look at how venture capital start-ups have funded innovation in the United States and its evolution during recessions and periods of growth over the last decades. They find that although patents filed by VC-backed start-ups are unconditionally of higher quality and economic value than the average patent, they are relatively more pro-cyclical than broad innovation. Early-stage companies during recessions apply for patents that are less cited, less original and further away from fundamental science. They point out that frictions on the supply side play an important role since venture capitalists tend to fund companies that are less risky and expand less in industries needing long-term commitments due to their fund structure. Other papers analyse both innovation and economic outcomes with a novel instrumental variable approach which uses the assignment of patent applications to examiners of different leniency. Farre-Mensa, Hegde, and Ljungqvist (2020) find that start-ups winning the patent "lottery" by receiving more lenient examiners have on average 55% higher employment growth and 80% higher sales growth within the next five years. A delay in the initial patent grant to a start-up has harmful effects in terms of growth, access to external capital and subsequent innovation. Conditional on the patents assigned being broad in scope, Hegde, Ljungqvist, and Raj (2021) find negative externalities on rivals' growth and innovative activities. Similarly, Gaulé (2018) looks at whether patent protection has a positive effect on start-ups access to VC funding and typical measures of entrepreneurial success such as IPO or premium acquisition relative to the amount of funding raised. Kogan, Papanikolaou, Seru, and Stoffman (2017) is a seminal paper on innovation and they build a patent-level measure of the private, economic value of individual patents based on the stock-market reaction to the granting event. This adds to the scientific value of individual patents which is generally captured by the number of citations that the patent obtains and their measure has significant predictive power towards firm growth. Other papers, such as Lindsey (2008a) or González-Uribe (2020) look into alliances and exchanges of innovation from the perspective of the VC investor. They find that strategic reasons on the VC side lead to complementary investments in an attempt of internalizing innovation spillovers and facilitating exchanges between portfolio companies. They find that companies joining a VC firm portfolio for the first time see a stark increase in measures of innovation exchange with other companies within the portfolio relative to non-joining similar start-ups.

A main direction of research related to ours is represented by papers looking into the entry of non-traditional players into the VC market. There are existing papers diving into the strategic reasons of investing in new ventures for established incumbent players (Ma, 2019). They find that incumbent firms entering the market via corporate venture capital (CVC) investments do so by acquiring stakes in firms with a similar technology focus and a non-overlapping knowledge base after the point where they experience a significant drop of their own innovation. Strategic value is then created for the incumbent player and CVCs are terminated when the innovation weakness is mended. Existing work, such as Chen and Ewens (2021) is closest to our focus looking into the constraints for start-ups seeing a reduction in the VC fundraising. This paper shows that in regions of the US outside main entrepreneurial hubs there is a disproportionate drop in financing and capital raised by start-ups. What our paper contributes to this already existing work is the deeper look into the anchoring role that banks play for individual companies, the abilities of banks to select successful investments and the innovation effects that happened in these under-served regions using a novel approach of teasing out variation at the start-up level from the attention received by start-ups before their first financing round. Our paper also uses this attention as an instrument to predict future innovative activity at the start-up level and future financing. Other recent papers such as Lerner, Mao, Schoar, and Zhang (2021) look at the use of alternative vehicles for start-up financing such as co-investments, parallel funds or feeder funds. They find that although alternative investment vehicles represent almost 40% of commitments in recent years, they tend to under perform the main funds and access to them is generally driven by preferential treatment offered by the general partners. Due to data availability, this will not be a focus of our paper, but we will exclusively focus on direct venture capital investments done through bank-affiliated VC funds.

Our paper is trying to exploit a different direction in which bank-affiliated VC funds are building value to. I try to fill a gap in the literature on private markets (focused on earlier stage, venture capital investments) regarding the role that banks play through their broad physical network, knowledge gained of the local markets and the ability to decrease financing risk[3] for

[3]Nanda and Rhodes-Kropf (2017) shows that having a deep-pocketed is positive since it provides liquidity in-

start-ups. A key novel result in the literature, to the best of my knowledge, is the fact that banks attract larger future investment rounds (at the company level), serving an anchoring role for the company during its VC life. I also look into detail into how bank investments positively affect innovation at the company level and provide evidence of a negative effect of banking regulation for local entrepreneurial communities.

3 Institutional setting and data

Having gained increased attention in the media due to the amendments it received, the Volcker Rule was initially implemented as part of the Dodd-Frank Wall-Street Reform and Consumer Protection Act. Brought forward by OCC, Board, FDIC, CFTC and SEC (hereafter, the Volcker Agencies) on December 10, 2013, the rule was initially intended to reduce risks in the banking system by generally restricting the ability of financial intermediaries (deposit-insured institutions) to engage in proprietary trading or sponsor private equity funds. A key element of the legislation was that banks were generally prohibited from owning, sponsoring or investing in private equity funds or hedge funds. To put the effect into perspective, according to Pitchbook, Goldman Sachs had 19% of its Tier 1 capital invested in private equity at the end of 2012. The rule only allowed banks to hold up to 3% of their core capital in covered funds, which broadly included multiple categories such as private debt funds, venture capital and others.

The rule stayed a long-time in the making in the lower house of Congress. In October 2011, the Volcker Agencies issued a Notice of Proposed Rulemaking requesting comments before implementing the Volcker legislation. The comment letters are available online, and can be found on the government's website.[4] After almost 1000 meetings with the agencies in order to discuss the rule, the legislation was finally passed on the 10th of December 2013. The rule itself arrived with a two year delay following its proposal and three years after the signing of the Dodd-Frank Act. The full implementation of the rule saw additional delays as some banking entities were granted additional provisions by the Fed until July 2015. These extensions were introduced in order to avoid market disruptions that might arise from bank's dumping covered assets into the marketplace (Krawiec & Liu, 2015). Following the implementation of the Rule, however, in 2018 the EGRRCPA Act was signed into law which limited compliance with the Volcker Rule for smaller

surance when times are bad and these abundance of financial resources helps start-ups take riskier, more innovative projects.

[4] Regulations.gov

banks with less than $10 billion in assets. Additional amendments built on EGRRCPA are implemented in 2019 and by October 2020 the Volcker Rule is repealed. The 2020 modification of the rule states that "Agencies believe [VC funds] may pose less potential risk to a banking entity sponsoring or investing in venture capital funds and to the financial system - specifically, the smaller role of leverage financing and to a lesser degree the interconnectedness with the public markets".[5]

In order to analyse the effects of this regulation on the venture capital sector in the United States I am taking advantage of data from VentureExpert, a commercial data provider part of Refinitiv, in accessing all the recorded venture capital investments obtaines by US-based companies since the mid 1960s. However, due to the quality of the recorded entries, for the specifications in which we look at the universe of VC transactions, we will focus on investments made after 1970. I will combine this main data set with several complementary data sources, all of which I will define in detail in the following sub-sections.

3.1 Venture capital data and investments

I use data from VentureExpert on company funding events with information on funding rounds, size, number and type of investors participating in every round and current company outcomes for all VC start-ups headquartered in the US which received funding between 1970 to 2020. I focus on funds which are defined as bank-affiliated where the bank plays thus the general partner (GP) role in the classical PE structure. The main data for the analysis is at the company-round level, meaning that we observe consecutive investments by the same fund, in the same company across multiple rounds. We also observe the size of the investor's syndicate in each individual round and the amount allocated by each investor in the round. We thus have data on the total amount of funds the company raised during its VC lifetime. We also take advantage of VC firm specific variables such as founding date, location or industry focus. From VentureExpert I also collect data on the fundraising activity of VC-focused funds located in the US between 2000 and 2020. I use the location, the volume and the type of funds in estimating the aggregate fundraising activity taking place after our shock and I add the GDP at the state-year level from US Bureau of Economic Analysis public database.

[5] Page 94: SEC.gov

3.2 Patent data and innovation

I use data on patent applications and on patent assignments from the USPTO Patent Assignment Dataset and USPTO Patent Examination Dataset (PatEx) which are disambiguated versions of the bulk download data available in raw format on the USPTO website. The Patent Assignment Dataset records the patent transfers by parties with the USPTO. A legal assignment transfers the rights, title and interest in a patent application from an owner (assignor) to a recipient (assignee). The dataset contains 9 million assignments recorded between 1970 and 2020 corresponding to 15 million patent applications. Many of the patent applications in the sample are assigned during the application process from the inventors, who own the patent rights to their employers, which is generally part of their contractual agreement. We observe data on the filing date of the patent from the Patent Examination Research Dataset (Patex) which will capture our main measure of raw innovation (Graham, Marco, & Miller, 2018; Marco, Myers, Graham, D'Agostino, & Apple, 2015). This is important since it has been discussed in previous papers such as Farre-Mensa et al. (2020); Hegde et al. (2021) that there are important financial consequences for the company due to the significant lag between application date and granted date. I also exploit the fact that patent applications started to be made public regardless of the grant status following the implementation of the American Inventors Protection Act (AIPA) in November 1999. Another significant piece of regulation introduced which concerns our patent data is the America Invents Act which went into effect on 16 March 2013 which made it possible to file applications directly in the name of the assignee and changed the system from a "first-to-invent" to a "first-to-file". I match data on successful application with data from Kogan et al. (2017) in order to obtain forward-looking citations and nominal values of innovation for the corresponding patents. I use the NBER Patent Data Project fuzzy name-matching algorithm to clean the company names and match the data on VC investments to the patent data based on the stem of the company name as in Hall, Jaffe, and Trajtenberg (2001).

3.3 Google Trends data

I wrote an automation script which downloaded the stem-name[6] Google Trends search results of 39,106 US-based start-up companies that raised financing between 1960-2020 from VentureExpert. Google Trends computes relative search interest in two categories: "Interest over time" and

[6] The algorithm of name-cleaning used to obtain the company stem is the one used in the NBER Patent Data Project by Hall et al. (2001) in order to clean assignee names before matching them to Compustat

"Interest by sub-region". I obtain for each company a monthly interest score and a geographical score corresponding to each of the 51 US states.[7] For the analysis, I keep companies which had their first VC investment date after 2004 since Google reports trends statistics from the beginning of that year. The aggregate results of this search can be seen in Figure 4. The heat-map captures the aggregated monthly-state level attention level to each company in the sample normalized by the maximum value for a month-state pair. GoogleTrends (GT) reports search interest relative to the highest point in time for a given company search at the monthly level. For a significant portion of the sample 46% for the state variable and 61% of the sample we have data on the GT attention variable.

4 Banks as VC investors

This section will compare VC investments the Midwest region of the United States against investments made in the rest of the country. The reason why this comparison is interesting is that the Midwest region is generally seen as a growing entrepreneurial region and as shown in the following analysis, relatively more dependant on bank financing at the VC stage. We aim to underline in this section the role that banks play as important investors in the VC market and their ability to screen highly successful companies. The states included in the Midwest category are as defined by the federal government Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin.

Table 1 presents t-statistics for the differences between companies which are located in the US Midwest vs. companies which are located in US non-Midwest regions. We observe that Midwest companies raise on average less funding, have a smaller number of investors throughout their VC life, are older on average at the first investment and are more dependent on bank financing relative to our non-Midwest sample. First investments are made less often during peaks of the credit market (Fang et al., 2013)[8] and more often during recessions. They are less dependant on average on independent PE firms, are getting acquired relatively less and are located in states which have on average a higher dependence on banks as investors in the VC market.

Table 2 presents mean statistics at the investment level for a sample of investments between

[7]The scores are computed relative to the maximum popularity of the term which will take the value of 100. Scores thus represent a relative grade in relation to the volume of the largest search in a month or state

[8]Defined for the specified sample as investments in the period 2005-2007 and represents an expansionary period of the private equity market in terms of the total volume of transactions.

2000 and 2020. An investment here is considered a unique match between a company and a VC firm. We only keep Bank affiliated VC investments and independent PE firms investments. For variables such as Age at Investment, PE Peak Year and NBER Recession Year we keep the date of the first investment. For the other variables we average across rounds at the company-VC firm level. Mean differences are reported between investments made by bank-affiliated VC funds in Midwest states vs. non-Midwest states. Looking first at the magnitude of coefficients for bank investments vs. independent PE firm investments we see that bank investments in the Midwest are larger in individual rounds, part of larger syndicates and finance companies which raise more funding. Bank investments are generally more successful relative to independent PE firm investments as measured by ratio of firms going public, being acquired or going through a merger, regardless of whether the investments are made in Midwest or not. A higher percentage of these investments is made during peaks of the PE market and also during recession periods. What is interesting to notice, however is the difference between bank investments in Midwest states vs. non-Midwest states. We see that they are statistically similar in size even though the total funding raised by the companies is largely different. This signals that banks have a preference for large investments which is different from the way PE firms are investing. Similarly to PE firms however, they invest in smaller syndicates, in earlier rounds and in companies which tend to be acquired less. However, these seem to be characteristics of the companies that are generally active in the Midwest. Another interesting result is that banks tend to invest in companies that are much older in Midwest (7 years at first investment) and thus tend to spend less time raising funding in the VC market.

The preferred specification used in Tables 3 and 4 is the following:

$$\text{Company Outcome}_i = \beta_0 + \beta_1 \text{Bank VC}_i + \text{Controls}_i + \Phi X_i + \varepsilon_i$$

Each observation corresponds to an individual entrepreneurial company and the dependant variable is the eventual outcome for company i. The specification is meant to disentangle in a cross-section of company outcomes whether bank VC investors have a positive ability in selecting successful investments. We do this relative to the other types of investors that the company might have in the VC market and by controlling for as many observable characteristics of the company as possible. The results seem to suggest that there is generally a strong positive correlation between having a bank as a VC investor and having a successful outcome.

Table 3 presents the result of a cross-sectional regression of companies outcomes on different types of investors that companies might have in the venture capital market. In the unreported list of controls I have included categories such as Angel Group, Individuals, Insurance Fund, PE Advisor, SBIC, University Program. I define a dummy variable equal to one and zero otherwise if the company had during its active period in the VC market either type of investors as part of its funding syndicate. Our measure of success captures the final outcome of the company being Acquired/IPO/Merger and the other variables are available for a sub-sample of start-ups matched to the USPTO data on patents. The value of patents is obtained from Kogan et al. (2017) for a subset of granted patents. We can see from this regression that having a bank as part of your investment syndicate is highly correlated with various success measures at the company level. This can either be the case if banks have superior investment-picking abilities or if they add value to the investments they make. Interesting to note as well is the fact that involvement of Government Affiliated VCs or Incubator (Development) Program VCs are generally predictive of failure at the individual company level. Also, relative to independent VCs, which are generally believed to be highly skilled in picking investments and have multiple advantages such as alliances Lindsey (2008b), bank VCs seem to be a stronger predictor of success for typical VC measures (IPO, Merger) but also much stronger in predicting future innovation measures such as patent applications, granted number of patents, citations received and economic value of these patents.

Table 4 looks similarly to the previous analysis at a cross-section of company outcomes and introduces a battery of fixed-effects in order to control for variation at the funding stage. Main interest variable here stays Bank VC which is a dummy equal to one if the company had received funding from at least one bank during its activity in the VC market. The intuition from the previous specification holds. Our estimates suggest that having a Bank investor in a syndicate is correlated with a 18% increase in the probability of success which is a 50% increase related to the unconditional mean of success. For our interaction of bank investment with Peak Year, where Peak Year represents a period of growth in the market as considered by Fang et al. (2013), we find a decrease in performance for investments made by banks during peak years, similar to the intuition from the mentioned paper and previous literature of cyclical underperformance of PE investments (Kaplan & Schoar, 2005). In the rest of the specification we include controls for total number of investors in the syndicate, average VC firm experience, number of new and follow on investments and the number of years that a company spends in the venture capital market. We see that having a bank as a VC investor has predictive power over the number of patent applications, grants, number of citations received for these patents and their value subject to the same set of controls and fixed effects.

5 Banks as anchor investors

In this section I show that banks serve an "anchoring" role for individual companies. I am using a panel of companies by rounds in order to show that for a company which receives an investment from a bank-affiliated fund during a round, the size of its next round will increase relative to a similar company without a bank VC investment. In order to do this I use a panel data regression with round number, size and company characteristics fixed effects. For the most strict specification I use Company ID fixed effects and I compare the coefficients with a propensity score matching specification approach. I find values similar in size, respectively a \$2 million average increase in the next funding round and a 0.5 bigger syndicate relative to a company without bank investments.

Table 5 presents a panel specification in a company-round level sample of observations. The specification shows that having a bank investor in a given round leads to a larger next round for that same company, in terms of size. This confirms the claim that banks serve as anchor investors to companies, attracting larger amount of funding in future rounds, possibly through a certification mechanism at the company level. Our main dependent variable $Bank\ VC_{t-1}$ is a lagged dummy variable indicating whether in that specific round there was an involved bank-affiliated VC investor. We include a battery of fixed effects controlling for the number of the lagged round, industry, company founded year and geographical location. Our most stringent specification is represented by column (4) and implies that the size of the immediately next round increases by almost \$2 million following a Bank VC investment. This is an economically significant magnitude given that the mean size of a round in our sample is around \$15 million. An alternative variable of interest to us is the firms dependance in a given round on banks as investors. We measure this with $BankDep._{t-1}$ as a ratio of the number of bank investors over total number of investors in a given round. We see that a one standard deviation increase in bank dependence in a round is correlated with 5.16% increase in the size of the next round which we consider an economically significant effect.

Table 6 shows a similar insight to the previous table for a different dependent variable, number of investors. We again use the same independent variables, number of bank VCs in a round, a dummy for bank VC investment and the logarithmic value of bank dependence to infer the increase that a Bank VC might bring for a future round. Columns (1) to (3) imply that one additional Bank VC in a given round leads to a 0.5-0.6 higher number of investors in the next round. We use a rich set of fixed effects to control for unobserved variation at the company level. The magnitude of the effect is considerable given that the average number of investors in a round in our sample is 3.

In order to infer whether banks simply invest in larger rounds and later in the lifetime of the company or whether they indeed add value in terms of funding (and attracting additional investors), we introduce a propensity score matching specification where company-rounds with bank investors are matched to a similar group of company-rounds without bank investors and the difference between their next funding round is compared. To do this, we run a PSM matching with no replacement for 1 and 3, 5, 10 matched companies. Our treatment variable will be $BankVC_{t-1}$ and our controls will be $SizeBucket_{t-1}$, $RoundNumber_{t-1}$, State, Industry, $AgeBucket_{t-1}$. The procedure finds a closely comparable group of company-rounds without treatment and estimates the average treatment effect on treated which is reported in Table 7. We see that the coefficients are strongly significant for the number of investors for all specifications but they lose significance for the size of the round when we have at least 10 matches. The magnitude of the coefficients is very close to the results obtained previously with our panel specification, respectively an approximately \$2 million and 0.5 investor increase in the next round following a bank VC investment.

6 Volcker Rule Shock

This section aims to provide causal evidence to the role that banks play as investors in the VC market. We look at a difference in difference scenario, around the implementation of the Volcker Rule at the VC fundraising activity taking place in the United States. We compute the average growth of bank VC investments at the state level before the implementation of the rule and we claim that it is positively correlated with the strength of the effect of the regulation. The reason for this is that, according to industry reports and practitioners' advice, it is mostly, the state which were growing in terms of bank VC financing (and in relative terms dependant on it) that were most strongly affected by the regulation. We indeed find that both the number of funds and the total volume of funding raised dropped following the introduction of the Volcker Rule, especially in states highly dependant on bank financing. The drop appears to be concentrated among the smaller section of the market. The preferred specification for this section is:

$$\text{State Fundraising}_{i,t} = \beta_0 + \beta_1 \text{Bank Dep}_i \times \text{Post}_t + \beta_2 \text{Bank Dep}_i + \beta_3 \text{Post}_t \\ + \beta_4 \text{GDP State}_{i,t} + \Phi X_i + \rho Z_t + \varepsilon_{i,t}$$

6.1 Fundraising level

Table 8 presents our results for the difference in difference specification. The Bank Dependence variable is computed at the state-level and it represents the average growth of the number of bank investments in our VC sample over 1980-2013. This measure should capture the fact that some states have seen a large growth in terms of bank investments in the VC market which should make them relatively more exposed to the Volcker shock. We expect to find negative coefficients in the post period for states that have seen a larger increase in bank financing in the VC market, thus that are highly bank dependant. Indeed, looking at a state-level specification, we observe a drop in the post period in terms of the number of funds raised in states that had a higher bank dependence. Controlling for the GDP of state at the yearly level does not change our coefficients. Splitting our sample for a narrower timing window or a top quartile compared to lowest quartile of bank dependence still keeps our coefficient significant. Furthermore, when looking at the state level amount of funding raised following the implementation of the Volcker Rule we see that the volume of funding raised at the state-level dropped as well. The specification holds as well when looking at a narrower time frame and when including state level GDP as a control variable.

We compute a dynamic specification of our regression where the dependant variable is the number of funds raised in a state during a year. We omit the year 2013 since we are interested to know how the fundraising changes relative to the last year before the implementation of the Volcker Rule. In Table 9 observe in columns (1) and (2) that the drop in fundraising happened after the introduction of the regulation. Furthermore, when splitting the sample into small, medium and large funds depending on their volume, we observe in column (3) that the largest drop has been seen in smaller funds.

Table 10 runs a similar difference in difference specification on a fund-level sample. We look at the volume of individual funds raised between 2008 and 2020. We similarly observe that in states which have seen a higher growth in bank financing the volume of funds raised in the post period (after 2014, following the Volcker Rule) decreases. The effects are statistically significant when we control for state GDP and we absorb variation for vintage year (funds that are raised in the same year) and sequence within firm (the order that the fund has within the fundraising activity of one firm). We also split the sample for a shorter period of time around the Volcker Rule and we exclude California from the sample and the coefficients remain significant.

Table A17 in the Appendix shows a dynamic drop of fundraising within a VC firm. I absorb the pre-Volcker Vintage year as being the last year in which a firm has raised a fund before the

Volcker Rule. We see the drop in fundraising is strongest before 2016 and after that point, the coefficients start to lose significance, possible due to a substitution that happened in the market in terms of funding. It is possible that new players have entered the VC market to substitute for the lost funding of banks being pushed out.

6.2 Company level outcomes

Similar to the previous subsection we exploit the implementation of the Volcker Rule as a shock to bank financing that differentially affected the companies located in states more dependant on bank financing. Here we look at the size of the financing companies receive in their first round before and after the introduction of the regulation. As we would expect, due to the lower amount of available financing, the size of the first rounds drops both in terms of volume and in the number of investors. Furthermore, we match a subsample of VC-funded companies to patent application data from USPTO and we find that the amount of innovation, as measured by the number of applications filed drops as well. We infer from this that the Volcker Rule had a disproportionately negative effect both on funding and innovation production at the company level especially for start-ups located outside main entrepreneurial clusters.

Table 11 looks at a difference in difference specification in a cross section of companies around the implementation of the Volcker Rule. The observations are at the company level and we focus on the characteristics of the first investment round. We control in our specification for state and year level fixed effects and we use both our measure of bank dependence that we previously introduced and a split of companies that are part of the top third vs. bottom third of the distribution. We find results to confirm our intuition from the previous section. Precisely, when looking at companies that raised funding before and after the Volcker Rule, we see a drop in the size of the first round and in the number of investors in the first round for companies located in states that were more dependant on bank financing at the VC stage. This confirms our intuition of the shock representing a differential drop in funding for some states relative to others. Thus, since the supply of capital in the market decreased, we see that in equilibrium the quantity of fundraising (both in terms of the number of investors involved and the amount of capital supplied) decreased. Focusing on a narrow period of time, around 2012-2016 still keeps our results positive, although the effect as expected decreases. Another interesting validity test is excluding California from the sample, which due to its large number of investors in the VC market, has both a low dependence on bank funding and a small growth rate of bank VC funding, which makes our effects stronger relative to column (5). A plot of the dynamic effect of the regulation can be seen in Figure 1. For a dynamic specification of the regression, similar to the results from Table 9 we see an immediate drop in funding in the first three year after the regulation is introduced followed by an slight increase in 2017 and 2018. We expect that it can be the case that additional investors have entered the market and filled the gap in supplied capital left by the exit of bank investors. This intuition is similar to the insight we obtain from Table **??** on the fund-level analysis where the drop in fundraising increases in the first three years after the regulation is introduced and the effect starts to diminish after that.

Table 12 takes the analysis one step further and uses the sample of company-year observations for those companies matched to our USPTO patent application data. We again keep the analysis for the default sample of observations between 2008-2020 where for each company we have matched the number of patent applications they submit in a given year, irrespective of the outcome of the application. We use this measure as our preferred measurement option of raw innovation. We use state and year of the application fixed effects to account for the unobserved heterogeneity of given years or unobserved variation of companies located within the same states. Column (1) provides our first result on the harmful externality that the Volcker Rule has had on innovation. We see that for states highly dependant on bank financing at the VC stage, there is a drop in the number of application for patents submitted by firms located in those states. Both the coefficient of Bank Dependence in column (1) and the interaction coefficient of column (2) which includes the effect of higher bank dependence show that unconditionally states with higher dependence on bank financing are states where firms innovate less. This is at odds with the fact that in the post period unconditionally we have seen a general increase in innovation in the sample (as seen from the coefficient on Post). Our specification is robust to alternative measures of bank dependence as presented in column (3) where we use the top third of companies in terms of bank dependence and to splitting the sample in alternative dimensions (excluding California or narrowing the time frame where we see an effect). In alternative robustness specifications we see that the effect on innovation is mainly concentrated in years following the Volcker Rule with a small lag. Respectively, the effect we find on innovation is mainly caused by a drop that happens after 2016 (a 2 year delay after the bank funding decreased). This effect can graphically be seen in Figure 2. The graph plots the coefficients of a dynamic regression similar to the one presented for the fundraising effect on the number of patent applications submitted by firms in the years around the implementation of the Volcker Rule. We omit 2013 as a year in the specification since the effects are computed relative to this year. We can see that the negative effect in concentrated in the latter years of the sample, where companies located in states which have seen a high growth of bank VC financing in the pre period are seeing a drop in innovation starting from 2016. We observe a similar recovery of the drop as in the fundraising specification, probably driven by the same channel of investor substitution over time.

7 Innovation in the Midwest

Using descriptive statistics I am aiming to show that the amount of raw innovation in the Midwest region overall has dropped in the recent years. I attribute this drop to the negative externality that the Volcker Rule has had on innovation, especially in these regions. Consistent with the previous section, the decrease in the amount of funding in areas highly dependant on bank financing at the VC stage has led to a drop in the number of patent applications (which we saw at the company level in Table 12) which in turn led to an aggregate stagnation in innovation for these states. We use data for our measure of raw innovation from Patex. We limit our patent applications to the the utility patents submitted by US inventors between 2008 and 2020. We define the regions that are part of the US Midwest similar to the body of the paper. We want to look at raw innovation as measured by the state of the inventor submitting the patent application. We have 2,160,307 unique patent applications submitted by 5,741,045 inventors. We count for each individual inventor the state of residence and we aggregate the measures at a monthly-state level depending on whether the inventors are located in Midwest or not. We normalize the number of application by the month before the rule went into full effect, March 2014. We exclude two outlier months for plotting purposes, however we keep them when computing the linear fit line. We see from Figure 3 that raw innovation for states in the Midwest has seen a drop in innovation following the implementation of the Volcker Rule. This comes to confirm the main story that our paper is trying to underline, the fact that the drop in bank financing, especially in states highly dependant on banks in the VC market (mostly Midwest states) has negatively affected innovation at a higher level. The reasoning for this is that those companies which would have benefited from financing from bank are now deprived of this financing source, which led to smaller rounds, smaller number of investors and subsequently less innovation. This underline the unexpected negative externalities that this regulation meant to reduce the risk-taking in the banking system as had on local, growing entrepreneurial systems.

7.1 Analysis using Google Trends attention

In this section I am using a novel dataset on attention paid to individual start-ups in the United States to predict the likelihood of innovation at the company level. I look at the attention a start-ups receives before its first VC financing round and I use this as an instrument in predicting the size of the first round it receives. Assuming that attention is only affecting patent applications through the effect on the financing companies receive (which is a valid claim considering that the price of applying and maintaining patents are significant), we are able to use attention as a valid instrument for innovation. We check further to see the validity of this instrument in our sample and we observe that companies in areas highly dependant on bank financing after the introduction of the Volcker Rule do not produce innovation while the effect still holds for companies in areas unaffected by the rule in the post period. We infer that the rule had indeed a negative effect at the start-up level by inhibiting the amount of innovation produced by individual companies.

I start with company-level attention proxies obtained from Google Trends. Descriptive statistics of the aggregate values at the state-month level can be seen in Figure 4. The variables are scaled relative to the highest value (within company) and averaged at the state-month level. We can see that the unconditional attention level is growing over the sample period and entrepreneurial hubs such as California, New York, Massachusetts appear at the top of the ranking. I match at the company level the monthly proxy for attention and the geographical attention by state. I keep for each company the attention values in the previous 12 months before the first investment date and the value of the attention in the state in which the company is headquartered. I compute the average attention value over the previous 12, 6, 3 months before the first VC investment date and the average growth rates for the same periods.

Table 13 presents an OLS specification at the company level. I keep the sample of companies with valid data on attention from Google Trends and which received their first VC round after 2004. The regression specification I use for this Table is the following:

$$\text{First VC Round Outcome}_{\,i,t} = \beta_1 \text{Attention GoogleTrends}_{i,t-k} + \Phi X_{i,t} + \varepsilon_{i,t} \tag{1}$$

I look at the number of investors that the company has in their first VC round as predicted by our company level measure of attention. I compute the average change in attention over the previous 12, 6, 3 months before the first venture capital round at the company level. A higher growth in our attention variables means that the company has attracted increased public attention in the period preceding our focal time point (the first VC investment date). We see as expected a positive relationship between the number of investors in the first round and the attention growth. The size of the coefficients is larger for longer horizons of attention preceding the first investment round and the specification is robust to including state, industry, investment year and age fixed effects.

Alternatively, I consider the size of the first round as our interest dependant variable in Table 14. I similarly see that a higher attention growth in the period preceding the first round leads to a higher amount invested in the company in its first round. The intention here is to prove that lagged attention serves as a strong instrument in predicting investment in a company. We are arguing that market attention to a specific company is a strong predictor of the amount of funding that the company will be able to raise. The specification is robust to including a battery of fixed effects and is significant across all 3 of our preferred horizons for attention.

In Table 15 I am building a two-stage least square specification where the probability of applying for a patent in the 6 months following the first VC round is our dependent variable. We use the size of the first founding round as our main explanatory variable but we are worried that its effect might be confounded by other factors such as firm performance which are difficult to measure at that point in time. For this reason, we instrument the size of the first round using the attention that the firms receive previous to this. Our claim here needed in order to satisfy the exclusion assumption is that our measure for attention does not affect the likelihood of applying for patents outside of the channel going through VC fundraising. We argue that this is the case indeed, since most of the start-ups would first need the funding obtained in the VC market in order to be able to afford the application fees for a patent. Moreover, it is the case as shown in the previous literature, that firms submit their applications for patents after their first VC round. We perform the 2SLS specification and we find the coefficient on the likelihood of applying for a patent in the following six month positive and significant. In column (5) and (6) we use the 2SLS specification to analyse the sample of companies located in states with high dependence on bank financing against companies located in states which were less dependent following the introduction of the Volcker Rule. We use our estimation to predict the effect of funding on innovation and we see that in states with a high dependence on bank financing, which thus suffered from a larger relative drop in funding, the effect is missing. In order words, in states where bank funding was an important source of financing at the VC stage, the mechanism we have proposed does not exist anymore due to the drop in financing, while in states less dependant on bank VCs we can still see a significant effect after the legislation.

In the appendix, in Figure 5 I provide the plotting of the reduced form for our 2SLS specification. We look at the predictive power of our attention measure (computed with a lag before the first VC investment round) on the likelihood that a company applies for a patent at different time horizons. Our claim here is that the channel through which that happens is due to the funding obtained by the company in the VC market. We see that the coefficients are predictive of an increased chance of applying for a patent up to 12 months following the first VC round with the strongest effects at a 6 months horizon. The specification controls for state and industry unobserved variation. The specification used is presented in the following regression. As a main explanatory variable I use the average growth in the Google Trends attention that the company receives in the 3/6/12 months preceding the first VC round.

$$\text{Patent Application}_{i,t+k} = \beta_1 \overline{\Delta}\text{Attention GoogleTrends}_{i,t-k} + \Phi X_i + \varepsilon_{it+k} \tag{2}$$

8 Conclusion

This paper has attempted to point out the importance of bank investors in the venture capital market. I underline the negative externalities arising from an individual piece of banking regulation. Looking around the implementation of the Volcker Rule, we observe negative consequences on firms dependent on bank VC financing in regions which previously saw strong entrepreneurial growth in terms of bank VC investments. We find a drop in the fundraising volume, a drop in the size of investments and a drop in innovation for companies active in the venture capital market. We claim that this drop has disproportionately affected regions outside main entrepreneurial hubs, such as California or Massachusetts and has impacted in particular growing VC ecosystems in the Midwest states. I use a novel measure of attention paid to these start-ups before their first VC financing round as an instrument in predicting company-level innovation. I observe that this mechanism fails to be significant following the implementation of the Volcker Rule in regions dependent on bank financing. I also look at the role that banks play in the US Midwest region as VC investors and I find an anchoring role for companies, attracting more investors and bigger future rounds. I find that banks are particularly skilled in screening and successfully exiting their VC investments as measured by classical measures of success from the literature such as acquisition or IPO. I also find that bank investors are strong predictors of success relative to other type of VC investors when looking at company innovation or real measures of success.

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Tables

Table 1: Summary statistics for midwest and non-midwest companies

	(1)	(2)	(3)	(4)
	Non-Midwest	Midwest		
	Mean	Mean	Mean Diff	p-value
Total Funding Volume	47.803	37.844	9.960**	0.011
Number Investors	6.280	5.188	1.091***	0.000
VC Activity (years)	3.421	3.293	0.128	0.129
Age at Investment (years)	4.202	6.376	-2.174***	0.000
Acquired (1/0)	0.261	0.220	0.041***	0.000
IPO (1/0)	0.054	0.048	0.006	0.185
Mean Age VC Firms	14.458	12.530	1.928***	0.000
PE Firm	0.651	0.603	0.047***	0.000
Bank VC	0.024	0.030	-0.005**	0.023
Bank Dependence State	0.038	0.042	-0.004***	0.000
PE Peak Year	0.320	0.280	0.040***	0.000
NBER Recession Year	0.095	0.109	-0.014**	0.022
Observations	26583	2515		

This table presents summary statistics at the individual company level. This sample considers all companies receiving their first VC round between 2000 and 2020. Total Funding Volume is the nominal million $ amount that a company raises in the VC market. Number Investors is the average size of the investor syndicate for a company during its VC lifetime. VC Activity (years) is the average number of years between the first and the last investment round for a company. Age at Investment (years) is the company age at the time it receives its first VC investment. Acquired/IPO are a set of dummies equal to one if the company went was acquired or went public by the end of the sample. Mean Age VC Firms is the mean age of the firms in the investor syndicates during the active period in the VC market. PE Firm is a ratio of the number of investors categorized as PE Firms over the total number of investors for a specific company. Bank VC is a ratio of the number of bank-affiliated VC investors over the total number of investors for a specific company. Bank Dependence State is the average bank dependence of companies located in the same state excluding the company itself. PE Peak Year is a dummy equal to one if the first investment received by the company was between 2005-2007. NBER Recession Year is a dummy equal to one if the first investment received by the company was between March 2001-November 2001, December 2007-June 2009. The states included in the Midwest category are as defined by the federal government Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin. The presented p-values are using a t-test for mean differences.

Table 2: Summary statistics for bank and independent VCs

	(1)	(2)	(3)	(4)	(5)	(6)
	PE Firm		Bank VC		(3)-(4)	p-value
	Non-Midwest	Midwest	Non-Midwest	Midwest		
VARIABLES	Mean	Mean	Mean	Mean	Mean Diff	
Investment Size	8.105	6.815	7.832	7.274	0.558	0.643
Round Size	20.71	15.31	31.44	20.70	10.736*	0.055
Total Funding Volume	85.27	55.59	110.8	57.73	53.088**	0.04
Number Investors	9.968	8.708	12.76	8.974	3.786***	0.000
VC Activity (years)	4.636	4.491	5.591	4.763	0.828**	0.013
Age at Investment (years)	4.408	5.625	5.204	7.169	-1.964***	0.000
Round Number	3.119	3.037	3.491	3.121	0.370**	0.021
Success (1/0)	0.370	0.319	0.498	0.459	0.04	0.244
IPO (1/0)	0.0792	0.0615	0.0978	0.117	-0.019	0.346
Merger (1/0)	0.00819	0.00904	0.0183	0.0173	0.001	0.913
Acquired (1/0)	0.291	0.258	0.401	0.342	0.059*	0.077
Mean Age VC Firms	15.22	13.39	19.00	16.77	2.228**	0.032
Follow On	8.172	6.818	10.64	7.203	3.442***	0.000
PE Peak Year	0.271	0.236	0.485	0.463	0.022	0.517
NBER Recession Year	0.0912	0.104	0.146	0.177	-0.031	0.195
Observations	74,339	5,528	3,549	231		

This table presents summary statistics of VC investments between 2000 and 2020. This sample considers all unique matchings between a VC firm and a company. We only keep Bank-affiliated VC investments and independent PE firm investments. For variables such as Age at Investment, PE Peak Year and NBER Recession Year we keep the date of the first investment. For the other variables we average across rounds at the company-VC firm level. Investment Size is the nominal million $ ammount that a VC firm invests in total in a company. Round Size is the average size in million $ of a round in which a PE firm or a Bank VC is taking part in. Total Funding Volume is the nominal million $ amount that a company raises in the VC market. Number Investors is the average size of the syndicate in which a Bank VC or PE Firm invests in. VC Activity (years) is the average number of years between the first and the last investment round for a company. Age at Investment (years) is the company age the first investment for Bank VCs and PE Firms. Round Number is the average round number of the investment. Success is a dummy variable equal to one and zero otherwise if the company has been acquired, went public or has been part of a merger by the end of the sample. IPO, Merger and Acquired are a set of dummies equal to one if the company went public, was merged or was acquired by the end of the sample. Mean Age VC Firms is the mean age of the firms in the investor syndicates for the two categories of investors. Follow On is the number of investors that invest across multiple rounds within the same company. PE Peak Year is a dummy equal to one if the first investment received by the company was between 2005-2007. NBER Recession Year is a dummy equal to one if the first investment received by the company was between March 2001-November 2001, December 2007-June 2009. The presented p-values are using a t-test for mean differences.

Table 3: OLS regression of company outcomes on VC types

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Success	IPO	Merger	Revenue	Employees	App. Patents	Granted Patents	Citations	Value Patents
Bank VC (0/1)	0.18***	0.08***	0.01***	97.70***	284.22***	10.20***	7.41***	15.23***	48.04***
	(0.01)	(0.01)	(0.00)	(25.84)	(85.87)	(2.52)	(1.92)	(2.30)	(4.50)
Corporate VC (0/1)	0.03**	0.01	-0.00	-93.14**	-370.10***	3.93***	2.74***	2.21	8.11*
	(0.01)	(0.01)	(0.00)	(32.87)	(92.72)	(0.75)	(0.53)	(1.28)	(4.38)
Government Affiliated VC (0/1)	-0.11***	-0.03***	-0.00	-59.94	-454.77***	3.39	2.30	-3.53***	11.45
	(0.02)	(0.01)	(0.00)	(43.06)	(57.79)	(2.79)	(1.93)	(0.96)	(12.95)
Incubator VC (0/1)	-0.15***	-0.05**	-0.00	-125.65***	-424.69***	-4.44***	-3.54***	-5.38***	-17.90***
	(0.02)	(0.02)	(0.00)	(26.88)	(90.95)	(0.90)	(0.65)	(1.26)	(5.17)
Independent VC (0/1)	0.13***	0.02*	0.01*	-90.83	-219.01	1.90***	1.38***	1.71***	2.90
	(0.01)	(0.01)	(0.00)	(86.12)	(160.01)	(0.54)	(0.36)	(0.33)	(4.88)
Constant	0.27***	0.06***	0.00*	349.01***	1,168.70***	4.14***	2.52**	5.38***	16.41***
	(0.01)	(0.01)	(0.00)	(91.45)	(119.53)	(1.17)	(0.91)	(0.96)	(3.33)
Observations	38,588	38,588	38,588	4,042	4,121	6,421	6,421	6,421	6,421
R-squared	0.08	0.06	0.01	0.04	0.05	0.05	0.05	0.02	0.02
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Age FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

This table presents the results of a cross-sectional regression of company outcomes on the different types of investors they might have in the venture capital market. The observations are at the individual company level. The sample of companies for the main analysis is corresponding to those companies founded between 1960 and 2020. The OLS regression is estimated using the following specification:

$$\text{Company Outcome}_i = \beta_0 + \beta_1 \text{Bank VC}_i + \text{Controls}_i + \Phi X_i + \varepsilon_i$$

Success is a dummy variable equal to one and zero otherwise if the company has been acquired, went public or has been part of a merger by the end of the sample. Revenue is the nominal million $ value of revenue that the company has received in the last available year, winsorized at 1%. Employees is the number of employees that the company hires in the last available year, winsorized at 1%. App. Patents is the number of patent applications submitted by the company for the sub sample of companies matched to USPTO data, winsorized at 1%. Granted Patents is the number of granted patent applications submitted by the company for the sub sample of companies matched to USPTO data, winsorized at 1%. Citations is the total number of citations received for all granted patent applications for the sub sample of companies matched to data from Kogan et al. (2017), winsorized at 1%. Value Patents is the nominal million $ value of granted patents for the sub sample of companies matched to data from Kogan et al. (2017), winsorized at 1%. The full list of independent variable included are in addition to the reported list Angel Group, Endowment and Pension Plan, Individuals, Insurance Fund, Investment Management Firm, Non PE Firm, PE Advisor, SBIC, Service Provider Firm, University Program. I define a dummy variable equal to one and zero otherwise if the company had during its active life in the VC market either type of investors as part of its VC funding syndicate. State FE are a set of dummies corresponding to each US state represented in the sample. Industry FE are a set of dummies corresponding to each of the 10 TRBC economic sectors. Age FE are a set of dummies corresponding to 4 age buckets for company's age at the first investment round. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All standard errors are clustered by State and Industry

Table 4: OLS regression of company outcomes on Bank VC

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Success	Success	Success	IPO	Employees	App. Patents	Granted Patents	Citations	Value Patents
Bank VC (0/1)	0.18***	0.02***	0.18***	0.07***	284.72***	6.74***	4.95***	12.29***	37.59***
	(0.01)	(0.00)	(0.01)	(0.00)	(80.09)	(1.28)	(0.92)	(1.28)	(2.09)
Peak Year (0/1)			0.14***	0.01***	-19.41	3.28***	2.68***	10.47***	27.41***
			(0.01)	(0.00)	(73.15)	(0.46)	(0.27)	(1.75)	(2.99)
Bank VC x Peak Year			-0.11***						
			(0.02)						
Constant	0.37***	0.40***	0.30***	0.04***	716.06***	3.30***	1.70***	0.94	0.11
	(0.00)	(0.00)	(0.01)	(0.01)	(59.85)	(0.33)	(0.27)	(2.79)	(3.64)
Observations	38,588	38,588	38,588	38,588	4,121	6,421	6,421	6,421	6,421
R-squared	0.07	0.20	0.09	0.06	0.08	0.08	0.08	0.02	0.02
State FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Age FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Size Funding FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Founded Year FE		YES							
Controls			YES	YES	YES	YES	YES	YES	YES

This table presents the results of a cross-sectional regression of company outcomes on a battery of controls and whether the company had a bank VC investor at the VC stage. The observations are at the individual company level. The sample of companies for the main analysis is corresponding to those companies founded between 1960 and 2020. The OLS regression is estimated using the following specification:

$$\text{Company Outcome}_i = \beta_0 + \beta_1 \text{Bank VC}_i + \beta_2 \text{Peak Year}_i + \beta_3 \text{Bank VC}_i \times \text{Peak Year}_i + \Phi X_i + \varepsilon_i$$

Success is a dummy variable equal to one and zero otherwise if the company has been acquired, went public or has been part of a merger by the end of the sample. Revenue is the nominal million $ value of revenue that the company has received in the last available year, winsorized at 1%. Employees is the number of employees that the company hires in the last available year, winsorized at 1%. App. Patents is the number of patent applications submitted by the company for the sub sample of companies matched to USPTO data, winsorized at 1%. Granted Patents is the number of granted patent applications submitted by the company for the sub sample of companies matched to USPTO data, winsorized at 1%. Citations is the total number of citations received for all granted patent applications for the sub sample of companies matched to data from Kogan et al. (2017), winsorized at 1%. Value Patents is the nominal million $ value of granted patents for the sub sample of companies matched to data from Kogan et al. (2017), winsorized at 1%. Peak Year is a dummy variable equal to one if the date of the first investment is between 1985-1989, 1998-2000, 2005-2007 corresponding to expansion periods of the PE market, as defined in Fang et al. (2013). Controls include a dummy variable for NBER recessions equal to one if the first investment took place between 1990-1991, March 2001-November 2001, December 2007-June 2009. Number Investors is a company specific variables representing the total number of VC investors. New and Follow On count the number of new or repeated investors in the company. Mean Firm Age represents the average age of the investors syndicate for a specific company. VC Activity Duration represents the rounded number of years that the company has been active in the VC market. State FE are a set of dummies corresponding to each US state represented in the sample. Industry FE are a set of dummies corresponding to each of the 10 TRBC economic sectors. Age FE are a set of dummies corresponding to 4 age buckets for company's age at the first investment round. Size Funding FE are a set of dummies corresponding to 4 size buckets for the total amount of funding the company has raised. Founded Year FE are a set of year dummies corresponding to the founding date of the company. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All standard errors are clustered by State and Industry

Table 5: Panel regression of round volume on lagged bank investment

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Round Size	Round Size	Round Size	Round Size	Log(Round Size)	Log(Round Size)
Nr Bank VCs_{t-1}	6.029***					
	(1.462)					
Bank VC_{t-1}(1/0)		7.054***	6.669***	1.978*		
		(1.541)	(1.492)	(1.008)		
Log(Bank Dep)$_{t-1}$					0.890***	0.905***
					(0.235)	(0.232)
Constant	13.907***	13.897***	13.956***	14.257***	15.386***	15.386***
	(0.071)	(0.092)	(0.086)	(0.037)	(0.004)	(0.004)
Observations	37,714	37,714	37,431	33,197	37,233	37,221
R-squared	0.156	0.149	0.190	0.619	0.216	0.220
Pre-Round Nr FE	YES	YES	YES	YES	YES	
Industry FE	YES	YES	YES		YES	
City FE	YES	YES			YES	YES
Vintage Year FE	YES	YES	YES		YES	YES
Age FE	YES					
Pre-Round Nr * Industry FE						YES
Company ID FE				YES		
Zip5 FE			YES			

This table presents a panel regression of financing volume in round t on the number of bank investors in the previous round. The observations are at the company-round level. The sample of companies used have received their first VC investment between 2000 and 2020. The regression is estimated using the following specification:

$$\text{Round Size}_{i,t} = \beta_0 + \beta_1 \text{Bank VCs}_{i,t-1} + \Phi X_{i,t-1} + \varepsilon_{i,t}$$

Round Size is the million \$ nominal amount of funding raised by company i in round t winsorized at 1%. Nr Bank VCs_{t-1} is the number of bank investors company i had in round t-1. Bank VC_{t-1} is a dummy which takes the value one if the company had at least one bank investor in round t-1. Log(Bank Dep)$_{t-1}$ is equal to log(1+BD_{t-1}) where BD is the share of bank investors from the total number of investors of company i in round t-1. Pre-Round Nr FE are a set of dummy variables for the lagged round number. Industry FE are a set of dummies corresponding to each of the 10 TRBC economic sectors. City FE are a set of dummies corresponding to each US city represented in the sample. Year FE are a set of year dummies corresponding to the first VC investment. Vintage Year FE are a set of dummy variables corresponding to the founding year of the company. Company Age FE are a set of dummies corresponding to 4 age buckets for company i at t-1. Zip5 FE represents the zip code level of the company's headquarter. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All standard errors are clustered by State and Industry

Table 6: Panel regression of round size on lagged bank investment

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Nr Investors	Nr Investors	Nr Investors	Log(Nr Investors)	Log(Nr Investors)
Nr Bank VCs$_{t-1}$	0.526***				
	(0.151)				
Bank VC$_{t-1}$(1/0)		0.626***	0.607***		
		(0.135)	(0.128)		
Log(Bank Dep)$_{t-1}$				0.199*	0.200*
				(0.101)	(0.103)
Constant	2.889***	2.888***	2.893***	1.235***	1.235***
	(0.011)	(0.011)	(0.009)	(0.002)	(0.002)
Observations	37,714	37,714	37,431	37,714	37,703
R-squared	0.119	0.119	0.150	0.107	0.109
Pre-Round Nr. FE	YES	YES	YES	YES	
Industry FE	YES	YES	YES	YES	
City FE	YES	YES		YES	YES
Vintage Year FE	YES	YES	YES		
Pre-Round Nr * Industry FE					YES
Zip5 FE			YES		

This table presents a panel regression of the number of investors in round t on the number of bank investors in the previous round. The observations are at the company-round level. The sample of companies used have received their first VC investment between 2000 and 2020. The regression is estimated using the following specification:

$$\text{Number Investors}_{i,t} = \beta_0 + \beta_1 \text{Bank VCs}_{i,t-1} + \Phi X_{i,t-1} + \varepsilon_{i,t}$$

Nr Investors is the number of funds that have invested in company i at time t. Log(Nr Investors) is equal to log(1+ Nr Investors). Nr Bank VCs$_{t-1}$ is the number of bank investors company i had in round t-1. Bank VC$_{t-1}$ is a dummy which takes the value one if the company had at least one bank investor in round t-1. Log(Bank Dep)$_{t-1}$ is equal to log(1+BD$_{t-1}$) where BD is the share of bank investors from the total number of investors of company i in round t-1. Pre-Round Nr FE are a set of dummy variables for the lagged round number. Industry FE are a set of dummies corresponding to each of the 10 TRBC economic sectors. City FE are a set of dummies corresponding to each US city represented in the sample. Year FE are a set of year dummies corresponding to the first VC investment. Vintage Year FE are a set of dummy variables corresponding to the founding year of the company. Zip5 FE represents the zip code level of the company's headquarter. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All standard errors are clustered by State and Industry

Table 7: PSM of round size on lagged bank investment

	Round Size	Nr Inv.	Round Size	Nr Inv.	Round Size	Nr Inv.	Round Size	Nr Inv.
ATT	2,26	0,50	2,14	0,48	2,06	0,50	1,43	0,43
se (ATT)	1,10	0,09	1,14	0,09	1,02	0,08	0,94	0,08
t-value	2,05838	5,435383	1,87967	5,157339	2,008499	5,901923	1,527359	5,479608
Nr_Obs	41027	41027	41027	41027	41027	41027	41027	41027
Matches	1	1	3	3	5	5	10	10

This table provides the estimate of the mean difference between the size of an "Anchor" round and the size of a "non-Anchor" round. Round Size is measured as the nominal million $ amount that the company is raising in that round and Nr Inv. represents the total number of investors providing funding in that round. We call an "Anchor" round a financing round which follows a round where at least one bank was part of the syndicate. "Non-Anchor" round is a comparable financing round which follows after a round with no bank investors. For the estimation of the propensity score, I estimate unreported Logit regressions where the dependent variable is Pre-Round-Bank VC which is a dummy variable equal to one if there is at least one bank investor in the respective VC round, zero otherwise. We use as independent variables the Pre-Round-Size which is a set of dummies corresponding to 4 bucket sizes for the equity raised in that round, winsorized at 1%. I use Pre-Round-Number which is a set of dummies corresponding to the number of the round. State which is a set of dummies corresponding to the 51 states in our sample. Industry which is a set of dummies corresponding to the 10 TRBC economics sectors from our sample. Pre-Round-Age is a set of dummies corresponding to 4 buckets for the age of the company at the time of the pre round. Near Neighbour N chooses the closest "non-Anchor" rounds with the nearest propensity scores and computes the arithmetic average of the N "non-Anchor" rounds in order to obtain the mean difference between the treated and control group. I report t-ratios for the average treatment effect on treated.

Table 8: DiD specification of fundraising on bank dependence

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Nr Funds All	Nr Funds All	Nr Funds 2011-2017	Nr Funds All	Vol Funds All	Vol Funds All	Vol Funds 2011-2017
Bank Dep. x Post	-0.738***	-0.745***	-0.518*		-1.533*	-1.539*	-2.387**
	(0.226)	(0.231)	(0.256)		(0.826)	(0.858)	(1.019)
GDP State		0.245				0.201	
		(1.240)				(4.160)	
Top Quart. Bank Dep. x Post				-0.325**			
				(0.152)			
Constant	1.728***	1.722***	1.630***	1.835***	5.145***	5.141***	5.141***
	(0.038)	(0.046)	(0.042)	(0.042)	(0.138)	(0.155)	(0.168)
Observations	371	371	198	174	371	371	198
R-squared	0.854	0.854	0.885	0.911	0.711	0.711	0.742
State FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

This table presents a difference in difference specification measuring the effect on the fundraising activity of our bank dependence variable around the Volcker Rule. The observations are at the state-year level. The sample of observations represents states with VC activity between 2008 and 2020. The OLS regression is estimated using the following specification:

$$\text{State Fundraising}_{i,t} = \beta_0 + \beta_1 \text{Bank Dep}_i \times \text{Post}_t + \beta_2 \text{Bank Dep}_i + \beta_3 \text{Post}_t + \beta_4 \text{GDP State}_{i,t} + \Phi X_i + \rho Z_t + \varepsilon_{i,t}$$

Number Funds$_{i,t}$ is equal to log(1 + N) where N is the number of funds raised in state i during year t. Volume Funds is equal to log(1 + $S) where S is the million nominal amount of funding raised in state i during year t. Bank Dependence is our continuous measure of average growth in the number of bank VC investments in a specific state. Post period is a dummy equal to 1 for the years following the implementation of the Volcker Rule in 2014. GDP State is the nominal value of GDP for state i at year t in million $. Top Quartile Bank Dependence is a dummy variable equal to 1 for the highest quarter of states based on the distribution of our Bank Dependence variable and 0 for the bottom quarter. State FE are a set of dummies corresponding to each US state represented in the sample. Year FE are a set of dummies corresponding to each year when a fund was raised. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All standard errors are clustered by State.

Table 9: Dynamic specification of a DiD regression of fundraising on bank dependence

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Nr Funds	Vol Funds	Nr Funds S	Nr Funds M	Nr Funds L
2008 x Bank Dep.	0.098	-0.577*	0.092	0.375**	-0.058
	(0.124)	(0.315)	(0.111)	(0.153)	(0.108)
2009 x Bank Dep.	-0.147	-1.138*	0.062	0.417**	0.347*
	(0.110)	(0.616)	(0.156)	(0.137)	(0.194)
2010 x Bank Dep.	-0.023	-0.409	0.046	0.047	0.034
	(0.111)	(0.437)	(0.174)	(0.106)	(0.091)
2011 x Bank Dep.	-0.040	-0.475	0.220	0.077	-0.012
	(0.108)	(0.346)	(0.186)	(0.163)	(0.111)
2012 x Bank Dep.	-0.337***	-0.632	-0.360*	0.053	0.099
	(0.103)	(0.527)	(0.194)	(0.138)	(0.116)
2014 x Bank Dep.	-0.260***	-1.073**	-0.349***	0.072	-0.340***
	(0.078)	(0.432)	(0.078)	(0.098)	(0.098)
2015 x Bank Dep.	-0.163	-0.368	-0.121*	-0.281**	-0.103
	(0.095)	(0.247)	(0.065)	(0.122)	(0.094)
2016 x Bank Dep.	-0.285***	-1.068***	-0.224*	-0.058	-0.348*
	(0.087)	(0.190)	(0.123)	(0.111)	(0.162)
2017 x Bank Dep.	-0.509***	-0.598	-0.487***	-0.390***	-0.173**
	(0.094)	(0.361)	(0.123)	(0.126)	(0.078)
2018 x Bank Dep.	-0.470***	-1.011***	-0.349**	-0.212*	-0.736***
	(0.074)	(0.291)	(0.131)	(0.099)	(0.149)
2019 x Bank Dep.	-0.258**	-0.358	-0.399***	-0.202	-0.363**
	(0.111)	(0.225)	(0.124)	(0.129)	(0.124)
2020 x Bank Dep.	-0.562***	-1.155***	-0.542***	-0.348**	-0.793***
	(0.100)	(0.346)	(0.167)	(0.119)	(0.085)
Constant	1.733***	5.249***	1.367***	1.284***	1.461***
	(0.014)	(0.102)	(0.031)	(0.016)	(0.021)
Observations	371	371	283	241	185
R-squared	0.860	0.714	0.752	0.837	0.912
State FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

This table presents a dynamic difference in difference specification measuring the effect on the fundraising activity of our bank dependence variable around the Volcker Rule. The observations are at the state-year level. The sample of observations represents states with VC activity between 2008 and 2020. The OLS regression is estimated using the following specification:

$$\text{State Fundraising}_{i,t} = \beta_0 + \sum_{t=2008}^{2020} \beta_t \text{Bank Dep}_i \times \text{Year}_t + \Phi X_i + \rho Z_t + \varepsilon_{i,t}$$

Number $\text{Funds}_{i,t}$ is equal to log(1 + N) where N is the number of funds raised in state i during year t. Volume Funds is equal to log(1 + \$S) where S is the million nominal amount of funding raised in state i during year t. Bank Dependence is our continuous measure of average growth in the number of bank VC investments in a specific state. 2013 is our reference category and is thus omitted. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All standard errors are clustered by State and Year.

Table 10: DiD specification of fund volume on bank dependence

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Fund Volume All	Fund Volume All	Fund Volume All	Fund Volume No CA	Fund Volume 2011-2017	Fund Volume Active VC
Bank Dep. x Post	-3.847***	-3.828***	-3.877***	-3.748***	-4.186***	-3.800***
	(0.489)	(0.489)	(0.494)	(0.618)	(0.653)	(0.481)
GDP State			-1.542			
			(3.227)			
Constant	4.311***	4.307***	4.367***	4.076***	4.177***	4.699***
	(0.054)	(0.054)	(0.128)	(0.079)	(0.072)	(0.064)
Observations	1,618	1,611	1,618	953	895	1,242
R-squared	0.134	0.151	0.134	0.172	0.180	0.113
Fund Sequence FE	NO	YES	NO	YES	YES	YES
Vintage FE	YES	YES	YES	YES	YES	YES

This table presents a difference in difference specification measuring the effect on the fundraising volume of our bank dependence variable around the Volcker Rule. The observations are at the individual fund level. The sample of observations represents funds raised between 2008 and 2020. The OLS regression is estimated using the following specification:

$$\text{Fund Volume}_{i,t} = \beta_0 + \beta_1 \text{Bank Dep}_i \times \text{Post}_t + \beta_2 \text{Bank Dep}_i + \beta_3 \text{Post}_t + \beta_4 \text{GDP State}_{i,t} + \Phi X_i + \rho Z_t + \varepsilon_{i,t}$$

Fund Volume is equal to log(1 + $S) where S is the million nominal amount of raised by fund i in year t. Bank Dependence is our continuous measure of average growth in the number of bank VC investments in a specific state. Post period is a dummy equal to 1 for the years following the implementation of the Volcker Rule in 2014. GDP State is the nominal value of GDP for each state at year t in million $. Fund sequence FE are a set of dummies corresponding to the order number of the fund within the firm that raised it. Vintage FE are a set of dummies corresponding to each year when a fund was raised. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table 11: DiD specification of financing round volume on bank dependence

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Size First Round All	Nr Investors First Round All	Size First Round All	Size First Round 2012-2016	Size First Round 2012-2016 (No CA)
Bank Dep x Post	-0.507***	-0.093*		-0.295**	-0.328**
	(0.144)	(0.051)		(0.112)	(0.132)
Top Third Bank Dep x Post			-0.140*		
			(0.074)		
Constant	1.603***	1.171***	1.609***	1.443***	1.314***
	(0.013)	(0.005)	(0.007)	(0.011)	(0.019)
Observations	15,347	15,347	12,268	5,992	3,619
R-squared	0.137	0.098	0.133	0.118	0.126
State FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

This table presents a difference in difference specification measuring the effect on the funding size in the first VC round of our bank dependence variable around the Volcker Rule. The observations are at the individual company level. The sample of companies for the main analysis is corresponding to those receiving their first VC investment between 2008 and 2020. The OLS regression is estimated using the following specification:

$$\text{Outcome First Round}_{i,t} = \beta_0 + \beta_1 \text{Bank Dep}_i \times \text{Post}_t + \beta_2 \text{Bank Dep}_i + \beta_3 \text{Post}_t + \Phi X_i + \rho Z_t + \varepsilon_{i,t}$$

Size First Round is equal to log(1 + \$S) where S is the million nominal amount of funding raised in the first VC round winsorized at the 1%. Nr Investors First Round is the log(1 + N) where N is the number of funds investing in the first round winsorized at 1%. Bank Dependence is our continuous measure of average growth in the number of bank VC investments in a specific state. Post period is a dummy equal to 1 for the years following the implementation of the Volcker Rule in 2014. Top Third Bank Dependence is a dummy variable equal to 1 for the highest third of companies based on the distribution of our Bank Dependence variable and 0 for the bottom third. State FE are a set of dummies corresponding to each US state represented in the sample. Year FE are a set of year dummies corresponding to the first VC investment. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All standard errors are clustered by State.

Table 12: DiD specification of patent applications on bank dependence

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Nr Applications All	Nr Applications All	Nr Applications All	Nr Applications No CA	Nr Applications 2010-2018 (No CA)
Bank Dep x Post	-0.181**	-0.337**		-0.233*	-0.249*
	(0.080)	(0.138)		(0.109)	(0.129)
Bank Dep	-0.155**				
	(0.066)				
Post	0.051***				
	(0.017)				
Top Third Bank Dep x Post			-0.090**		
			(0.038)		
Constant	1.123***	1.154***	1.150***	1.096***	1.105***
	(0.014)	(0.031)	(0.024)	(0.016)	(0.018)
Observations	11,976	11,976	10,394	6,334	4,727
R-squared	0.006	0.009	0.006	0.035	0.035
State FE	NO	NO	NO	YES	YES
Year Application FE	NO	YES	YES	YES	YES

This table presents a difference in difference specification measuring the effect on the number of patent applications submitted by individual companies of our bank dependence variable around the Volcker Rule. The observations are at the company-year level. The sample of companies for the main analysis is corresponding to those receiving their first VC investment between 2008 and 2020. The OLS regression is estimated using the following specification:

$$\text{Number Applications}_{i,t} = \beta_0 + \beta_1 \text{Bank Dep}_i \times \text{Post}_t + \beta_2 \text{Bank Dep}_i + \beta_3 \text{Post}_t + \Phi X_i + \rho Z_t + \varepsilon_{i,t}$$

Number $\text{Applications}_{i,t}$ is equal to log(1 + N) where N is the number of submitted applications in a given year t by company i winsorized at 1%. Bank Dependence is our continuous measure of average growth in the number of bank VC investments in a specific state. Post period is a dummy equal to 1 for the years following the implementation of the Volcker Rule in 2014. Top Third Bank Dependence is a dummy variable equal to 1 for the highest third of companies based on the distribution of our Bank Dependence variable and 0 for the bottom third. State FE are a set of dummies corresponding to each US state represented in the sample. Year FE are a set of year dummies corresponding to the years of the patent application. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All standard errors are clustered by State.

Table 13: OLS regression of first round size on Google Trends attention

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Nr Inv. First Round	Nr Inv. First Round	Nr Inv. First Round	Nr Inv. First Round	Nr Inv. First Round	Nr Inv. First Round
Attention growth (-12m)	0.532***			0.443***		
	(0.098)			(0.091)		
Attention growth (-6m)		0.337***			0.275***	
		(0.058)			(0.050)	
Attention growth (-3m)			0.256***			0.209***
			(0.075)			(0.059)
Constant	2.339***	2.350***	2.355***	2.348***	2.357***	2.361***
	(0.007)	(0.005)	(0.006)	(0.006)	(0.004)	(0.005)
Observations	4,567	4,567	4,567	4,552	4,552	4,552
R-squared	0.037	0.036	0.037	0.080	0.079	0.080
State FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE				YES	YES	YES
Company Age FE				YES	YES	YES

This table presents an OLS regression of the number of investors in the first VC round on the attention measure from Google Trends. The observations are at the individual company level. The sample of companies is corresponding to investments made between 2004 and 2020, the period when the Google Trends attention variable exists. The regression is estimated using the following specification:

$$\text{Nr Inv. First Round}_{i,t} = \beta_0 + \beta_1 \overline{\Delta}\text{Attention GoogleTrends}_{i,t-k} + \Phi X_{i,t} + \varepsilon_{i,t}$$

Nr Inv. First Round is the number of funds investing in the first round. Attention growth (-tm) is the average change in the attention the company received in the previous t months. State FE are a set of dummies corresponding to each US state represented in the sample. Industry FE are a set of dummies corresponding to each of the 10 TRBC economic sectors. Year FE are a set of year dummies corresponding to the first VC investment. Company Age FE are a set of dummies corresponding to the rounded age in years between the company founding date and the first investment. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All standard errors are clustered by State.

Table 14: OLS regression of first round volume on Google Trends attention

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Size First Round	Size First Round	Size First Round	Size First Round	Size First Round	Size First Round
Attention growth (-12m)	0.741***			0.518***		
	(0.153)			(0.136)		
Attention growth (-6m)		0.437***			0.327***	
		(0.086)			(0.082)	
Attention growth (-3m)			0.187**			0.132**
			(0.076)			(0.064)
Constant	1.704***	1.722***	1.740***	1.716***	1.727***	1.741***
	(0.011)	(0.007)	(0.007)	(0.010)	(0.006)	(0.006)
Observations	4,567	4,567	4,567	4,552	4,552	4,552
R-squared	0.077	0.072	0.066	0.182	0.181	0.177
State FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE				YES	YES	YES
Company Age FE				YES	YES	YES

This table presents an OLS regression of the dollar size in the first VC round on the attention measure from Google Trends. The observations are at the individual company level. The sample of companies is corresponding to investments made between 2004 and 2020, the period when the Google Trends attention variable exists. The regression is estimated using the following specification:

$$\text{Size First Round}_{i,t} = \beta_0 + \beta_1 \overline{\Delta}\text{Attention GoogleTrends}_{i,t-k} + \Phi X_{i,t} + \varepsilon_{i,t}$$

Size First Round is equal to log(1 + $S) where S is the million nominal amount of funding raised in the first VC round. Attention growth (-tm) is the average change in the attention the company received in the previous t months. State FE are a set of dummies corresponding to each US state represented in the sample. Industry FE are a set of dummies corresponding to each of the 10 TRBC economic sectors. Year FE are a set of year dummies corresponding to the first VC investment. Company Age FE are a set of dummies corresponding to the rounded age in years between the company founding date and the first investment. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All standard errors are clustered by State.

Table 15: 2SLS regression of patent application on round size

	(1)	(2)	(4)	(5)	(6)
VARIABLES	Next App. 6m OLS	Size First Round First Stage	Next App. 6m 2SLS	Next App. 6m Post: High Dep.	Next App. 6m Post: Low Dep.
Size First Round (IV)			0.145**	0.184	0.283***
			(0.070)	(0.524)	(0.067)
Size First Round	0.031***				
	(0.007)				
Attention growth (-6m)		0.327***			
		(0.094)			
Constant	0.118***	1.763***			
	(0.013)	(0.009)			
Observations	3,275	3,271	3,271	267	1,324
R-squared	0.051	0.210	-0.077	-0.090	-0.367
State FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
Age FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

This table presents a 2SLS regression of the likelihood of applying for a patent within 6 months after the first VC round on the size of the first VC round. The instrument we are using is the average change in attention the company received in the 6 months previous to the first VC round. The exclusion assumption here is that patent applications are affected by attention only through the increase in VC funding received in the first round. We test this mechanism following the implementation of the Volcker Rule in states with high bank dependence vs. low bank dependence and we find significance only in the latter case. The sample of companies is corresponding to first investments made between 2004 and 2020, the period when the Google Trends attention variable exists. The regression is estimated using the following two specifications:

$$\text{Size First Round}_{i,t} = \beta_0 + \beta_1 \overline{\Delta}\text{Attention GoogleTrends}_{i,t-6} + \Phi X_{i,t} + \varepsilon_{i,t}$$

$$\text{Patent Application}_{i,t+6} = \beta_0 + \beta_1 \overline{\Delta}\widehat{\text{Size First Round}}_{i,t} + \Phi X_{i,t} + \varepsilon_{i,t}$$

Next App. 6m is a dummy variable equal to 1 if the company submitted a patent application in the following 6 months after the first VC round. Size First Round is equal to log(1 + $S) where S is the million nominal amount of funding raised in the first VC round. Attention growth (-tm) is the average change in the attention the company received in the previous t months. State FE are a set of dummies corresponding to each US state represented in the sample. Industry FE are a set of dummies corresponding to each of the 10 TRBC economic sectors. Company Age FE are a set of dummies corresponding to the rounded age in years between the company founding date and the first investment. Year FE are a set of year dummies corresponding to the first VC investment. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All standard errors are clustered by State.

Table 16: OLS regression of next patent application date on Google Trends attention

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	App. 3m	App. 3m	App. 3m	App. 6m	App. 6m	App. 6m	App. 12m	App. 12m	App. 12m	App. 24m	App. 24m	App. 24m
Attention growth (-12m)	0.01			0.05*			0.05**			0.02		
	(0.02)			(0.02)			(0.02)			(0.02)		
Attention growth (-6m)		0.02*			0.04*			0.04**			0.02	
		(0.01)			(0.02)			(0.02)			(0.02)	
Attention growth (-3m)			0.02**			0.03**			0.02**			0.01
			(0.01)			(0.01)			(0.01)			(0.02)
Constant	0.08***	0.08***	0.08***	0.16***	0.16***	0.17***	0.31***	0.31***	0.31***	0.51***	0.51***	0.51***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	4,567	4,567	4,567	4,567	4,567	4,567	4,567	4,567	4,567	4,567	4,567	4,567
R-squared	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.02	0.02
State FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

This table presents an OLS regression of the probability of applying for a patent on the attention measure from Google Trends. The observations are at the individual company level. The sample of companies is corresponding to investments made between 2004 and 2020, the period when the Google Trends attention variable exists. The focal point t is represented by the month of the first received VC investment. The regression is estimated using the following specification:

$$\text{Patent Application}_{i,t+k} = \beta_0 + \beta_1 \overline{\Delta}\text{Attention GoogleTrends}_{i,t-k} + \Phi X_i + \varepsilon_{i,t+k}$$

App. tm is a dummy variable equal to 1 if the company submitted a patent application in the following t months after the focal point. Attention growth (-tm) is the average change in the attention the company received in the previous t months. State FE are a set of dummies corresponding to each US state represented in the sample. Industry FE are a set of dummies corresponding to each of the 10 TRBC economic sectors. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All standard errors are clustered by State.

Figures

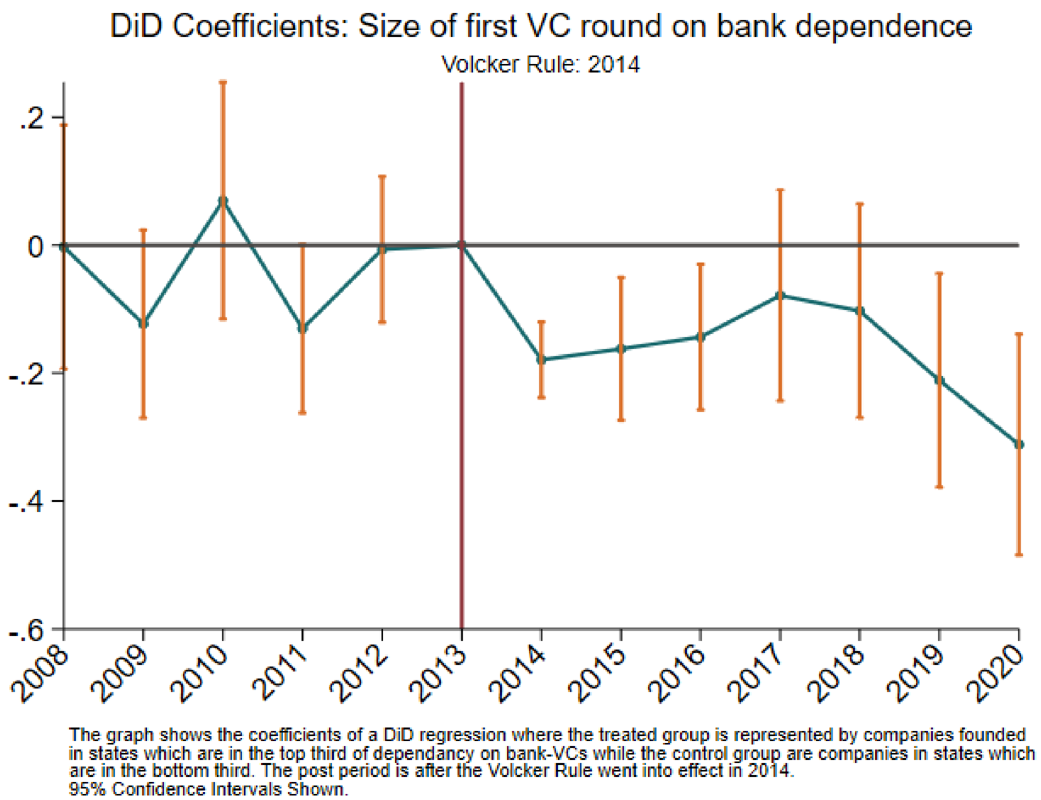
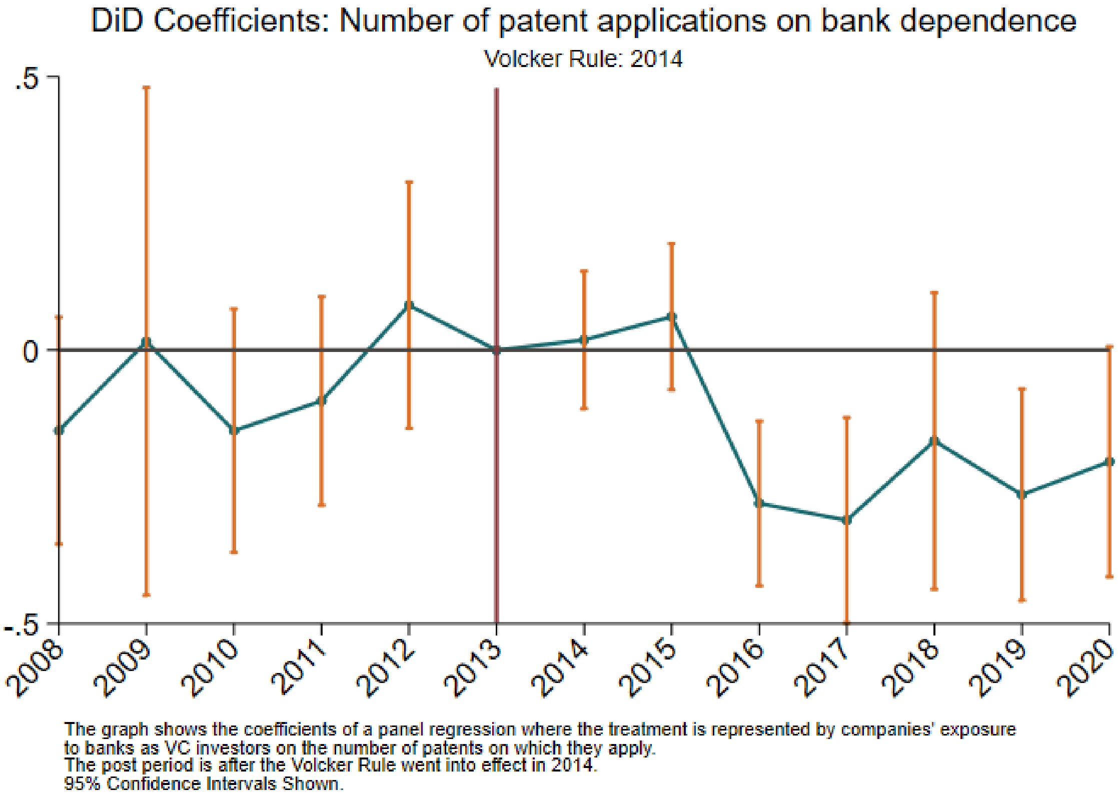


Figure 1: This graph plots the coefficients of a dynamic version of the regression presented in Table 11. We regress the size of the first VC round received on a set of dummy years corresponding to the first VC investment received by each company interacted with our measure of dependence on bank financing. The omitted category are companies receiving their first VC round in 2013. The intuition is that companies in states more dependent of bank VC financing are more more strongly impacted by the introduction of the Volcker Rule. We observe that the drop in the size of the first VC round is significant immediately after the regulation is introduced and reverses back to its previous level in 2017. The dynamic specification uses state and year fixed effects and clusters the standard errors at the state and year level.



[!h]

Figure 2: This graph plots the coefficients of a dynamic version of the regression presented in Table 12 looking at the fundraising effect on the number of patent applications submitted by firms in the years around the implementation of the Volcker Rule. We omit 2013 as a year in the specification since the effects are computed relative to this year. We can see that the negative effect is concentrated in the latter years of the sample, where companies located in states which have seen a high growth of bank VC financing before the Volcker Rule are seeing a drop in innovation starting from 2016. We observe a similar recovery of the drop as in the fundraising specification, probably driven by a similar investor substitution channel over time.

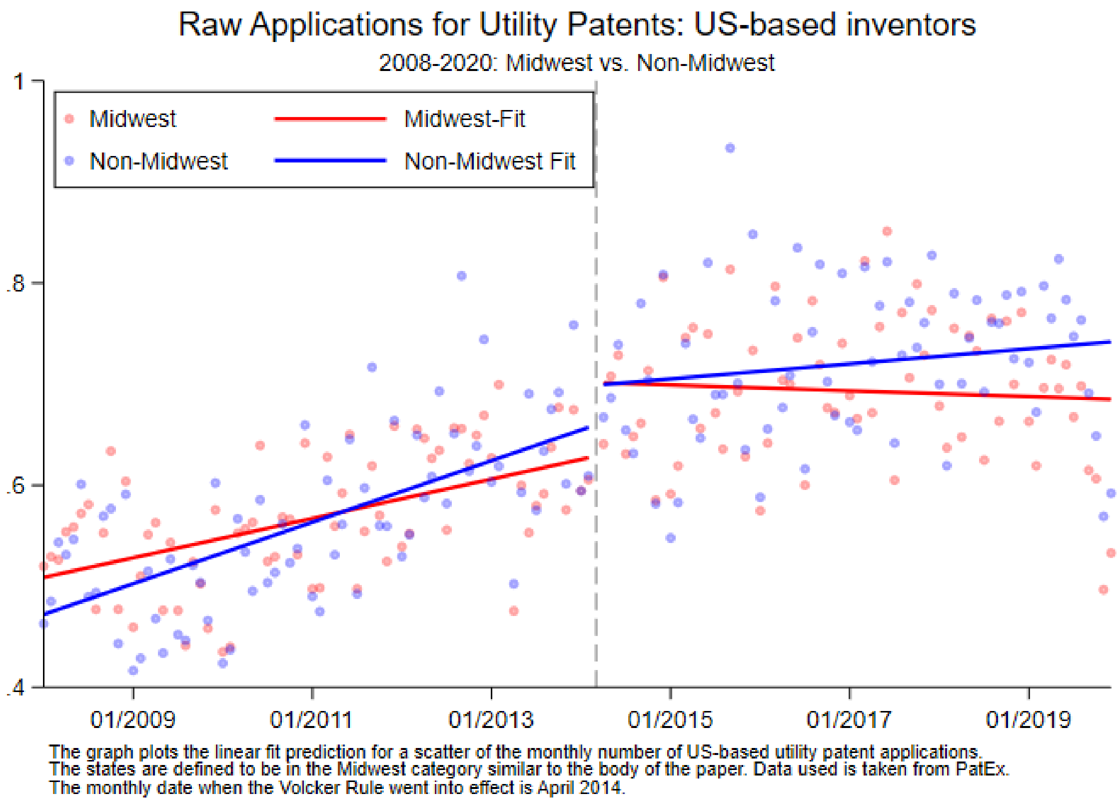


Figure 3: The graph plots the number of utility patent applications submitted by inventors located in the United States. The applications are aggregated on a monthly level depending on the state of residence of the individual inventor. Data used is obtained from PatEx which is a disambiguated version of the data available from the USPTO Public Pair database(Graham et al., 2018). PatEx records all patent application submissions after 2001 regardless of the granted status. I split the states in the Midwest and non-Midwest sample similar to the body of the paper. For illustration purposes, two months with outlier values (2013m3 and 2014m3) were left out for illustration purposes. However, the values were kept when computing the scaling and the linear fit prediction.

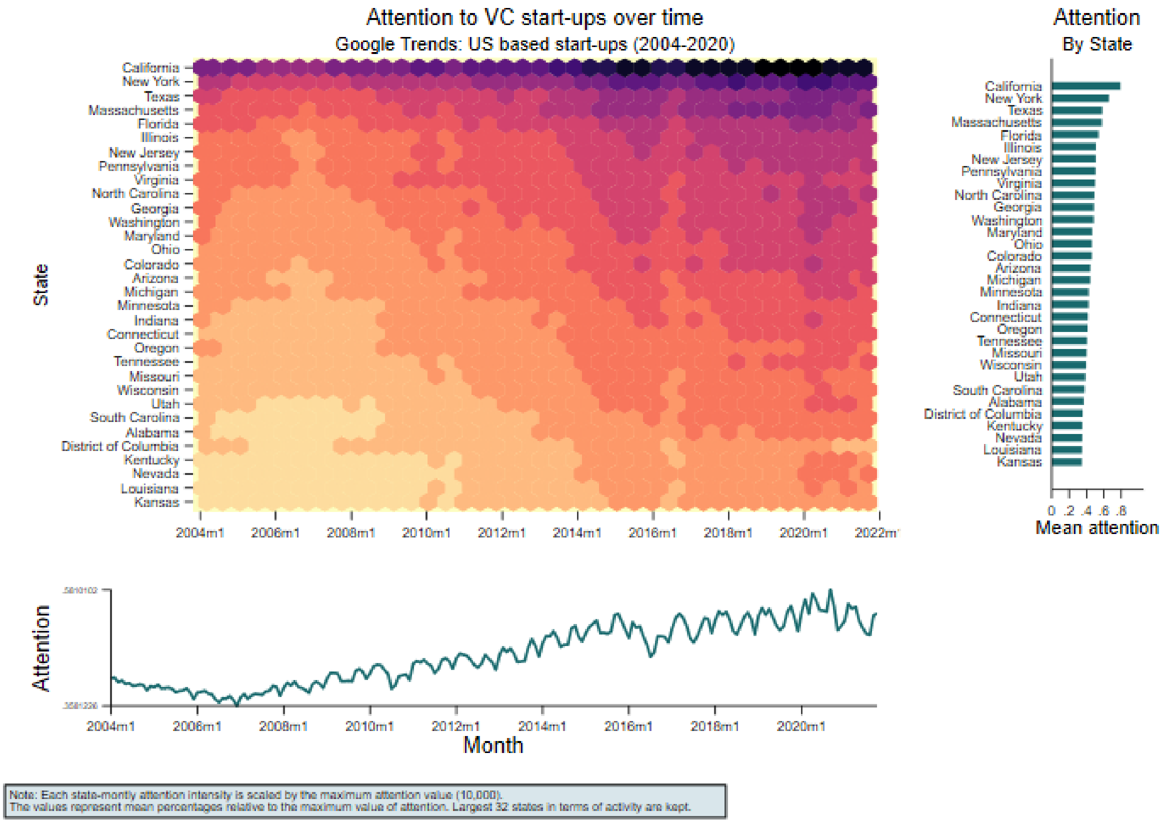


Figure 4: I coded an automation script which uses Google Trends to search the stem-name (the algorithm of name-cleaning used to obtain the stem is the one used in the NBER Patent Data Project[9] in order to clean assignee names before matching them to Compustat) of 39,106 US-based start-up companies which raised capital between 1960-2020 from VentureExpert. Google Trends computes relative search interest in two categories:"Interest over time" and "Interest by sub-region". I obtain for each company a monthly interest score and a geographical score corresponding to each of the 51 US states (the scores are computed relative to a maximum popularity which will take the value of 100). I keep companies which had their first VC investment date after 2004 since Google reports trends statistics from the beginning of that year. The heat-map captures the aggregated monthly-state level attention value to each company in the sample normalized by the maximum value for a month-state pair. For a significant portion of the sample, 46% for the state variable and 61% for the monthly variable we have data on the GoogleTrends attention.

Appendix

Table 17: OLS regression of fundraising by year on bank dependence

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	By 2014	By 2015	By 2016	By 2017	By 2018	By 2019	By 2020
Bank Dep.	-0.168*	-0.203*	-0.327**	-0.314**	-0.236*	-0.232*	-0.237*
	(0.094)	(0.120)	(0.129)	(0.136)	(0.124)	(0.120)	(0.122)
Constant	0.176***	0.318***	0.445***	0.481***	0.526***	0.548***	0.561***
	(0.021)	(0.027)	(0.029)	(0.037)	(0.032)	(0.036)	(0.037)
Observations	623	623	623	623	623	623	623
R-squared	0.030	0.024	0.037	0.049	0.061	0.064	0.071
Pre-Volcker Vintage FE	YES	YES	YES	YES	YES	YES	YES

This table presents an OLS specification measuring the effect on the likelihood of raising a new fund of our bank dependence variable after the Volcker Rule. The observations are at the individual firm level. The sample of observations represents firms which raised funds between 2008 and 2020. The OLS regression is estimated using the following specification:

$$\text{Firm raised fund by}_{i,t} = \beta_0 + \beta_1 \text{Bank Dep}_i + \rho Z_t + \varepsilon_{i,t}$$

By t is a dummy variable equal to 1 if firm t has raised a new fund until year t. Bank Dependence is our continuous measure of average growth in the number of bank VC investments in a specific state. Pre-Volcker Vintage FE is a set of dummies corresponding to the last year when a specific firm has raised a fund in the pre Volcker period. *** p<0.01, ** p<0.05, * p<0.1.

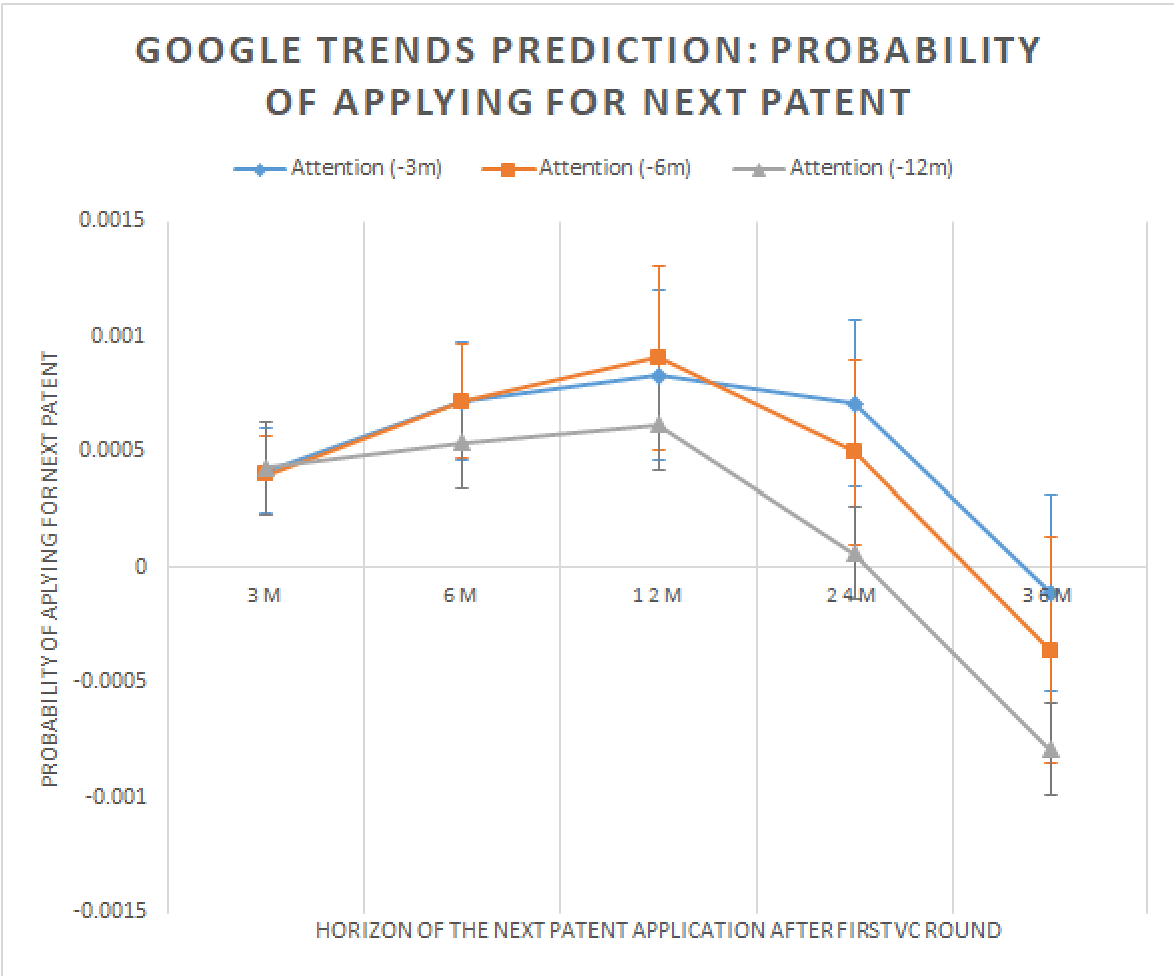


Figure 5: The figure plots the coefficients and the standard errors from a similar regression to the one presented in Table 16. We compute the predictive power of our lagged Google Trends attention variable over different time horizons in which the company could apply for a patent. The analysis is relative to a company specific focal point, which is the date of its first VC investment round. We observe that the predictive power is strongest up to a 1 year horizon after which the lagged attention loses its statistical significance.