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# Essays in Entrepreneurial Finance

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*Author:*
Silvia DALLA FONTANA

*Supervisor:*
Prof. Laurent FRÉSARD

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*Dissertation Committee:*

Prof. Laurent FRÉSARD, Università della Svizzera italiana and SFI
Prof. Francesco FRANZONI, Università della Svizzera italiana and SFI
Prof. Gordon PHILLIPS, Tuck School of Business, Dartmouth College

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# Abstract

The chapters of my dissertation analyze the financing of high-growth startups and the frictions these firms encounter in securing funding from Venture Capital (VC) investors. VCs have played a pivotal role in financing groundbreaking innovations over the past few decades, becoming the gatekeepers of success for many high-growth technological companies.

Chapter 1, Entry and Specialization in the VC industry, investigates the VCs' choice to specialize in specific sectors, and the impact of such choices on the entrepreneurial landscape. I document that VC specialization, measured as the HHI of capital invested across sectors, has increased by 30% since 2006. This increase is mainly driven by new VC funds focused on the booming software sector which was enabled by a technological shock to the cost of starting software-related businesses. In fact, specialization in software-focused VCs increased by 50%, compared to 10% in other sectors. To test whether this specialization is a response to reduced entry costs, I analyze the impact of Amazon Web Services (AWS) introduction in 2006. AWS significantly lowered entry costs for software startups by providing cheaper computing resources and storage through the cloud. I argue that new VCs that have limited resources and seek fast-reputation building, are drawn to sectors offering abundant opportunities and lower experimentation costs. Indeed, my findings reveal a significant increase in first-time investors financing software-related businesses following the introduction of cloud computing. Aligned with frictions arising from search and matching, I show that overall this higher focus on software by VCs appears to have had a negative funding spillover on startups that did not benefit from the technological shock. These results suggest one potential mechanism for the documented decline in non-software investments in recent years and shed light on the potential real effects of VC-firm specialization.

In Chapter 2, From in-person to online: the new shape of the VC industry, co-authored with Liudmila Alekseeva, Caroline Genc, and Hedieh Rashidi Ranjbar, we ask whether geographical clustering and in-person interactions remain crucial in the VC industry amidst the rise of online communications. VCs mostly rely on soft information when evaluating startups. As soft information cannot reliably be transferred through distance, in-person interactions between VCs and startups have always been considered necessary. However, online communication has enabled more remote relationships over the past decades, gradually reducing geographical constraints. Despite this, in the VC industry strong geographical clustering persisted. We test how

VCs respond to an unexpected interruption in face-to-face meetings during the Covid-19 pandemic and document that they break their traditional norm and invest in more distant startups. We find that distance post-Covid exhibits a rise of 35% between a VC firm and its portfolio company in a cross-section of all first-round VC investments. At the same time, VCs balance the lack of soft information with their own expertise and choose businesses that are more similar to past investments. We also find that the VCs' syndication process is affected by this new environment: Post-Covid, VCs rely more on their existing network. Overall, our findings suggest that online interactions do not entirely substitute for in-person ones and may not overcome frictions associated with distance for most VC investors.

Finally, in Chapter 3, Innovating to Net Zero, co-authored with Ramana Nanda and published in the *Entrepreneurship and Innovation Policy and the Economy journal*, we investigate the role of VC financing of climate change related technologies. We provide evidence that patents related to clean energy generation and storage, industrial production, and carbon capture and sequestration, are more than twice as likely to cite fundamental science than other Net-Zero related patents, highlighting their *deep tech* focus compared to innovation in areas such as energy efficiency, ICT and transportation. VC-backed firms stand out for their patents' likelihood to cite fundamental science compared to other firms, particularly within these *deep tech* sectors. Net-Zero patents granted to VC-backed firms are also three-to-five times more likely to be among the most cited patents, indicating the distinctive nature of innovations commercialized by VC-backed firms. However, VC's contribution to Net Zero patents remains relatively small, and the patenting focus of VC-backed firms has shifted away from *deep tech* in recent years. We discuss the growing literature on the potential frictions facing the commercialization of science-based *deep tech* innovations and touch on potential solutions that might enable VC to play a more meaningful role in supporting the transition to Net Zero in the coming decades.

# *Acknowledgements*

Form the start of my PhD journey, I've been told that a PhD is not a sprint but a marathon. Perhaps curious to see if the comparison held true, I took up running. After gaining experience as a doctoral student and ultra-marathon runner, I can now say that a PhD is more like a *mountain ultramarathon*. In both, trusting the journey is key to progress. At the bottom of the steepest climbs, especially near the end, the summit can feel impossibly distant. Yet, reaching that final peak brings the deepest sense of joy. Crossing the finish line, after hours of physical and mental trials, is pure bliss. But, just like in any ultramarathon, you never reach the finish line alone. With that in mind, I want to take a moment to thank the wonderful people I've been lucky enough to meet along the way in this wildest of ultramarathons.

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# Contents

# 1 Entry and Specialization in the VC industry

## 1.1 Introduction

Venture capitalists (VCs) have played a pivotal role in financing groundbreaking innovations over the past few decades, becoming the gatekeepers of success for many high-growth technological companies. Despite accounting for less than 0.5 percent of new firms created annually in the United States, nearly half of the entrepreneurial firms that make it to the public markets are VC-backed (Lerner and Nanda, 2020). Investing in startups entails high levels of asymmetric information, and VCs can mitigate such informational frictions by acquiring sector-specific knowledge through investments focused on a few sectors. In fact, in their recent survey, Gompers, Gornall, et al., 2020 report that 61% of VCs indicate that they specialize in specific sectors. Yet, the literature has remained largely silent on the determinants of this specialization choice, its evolution over time, as well as its impact on startups. This paper aims to answer these questions.

I document that the sectoral specialization of VCs has significantly increased in recent years. Measured using a Herfindahl-Hirschman Index of concentration of capital invested across different sectors, the average specialization of VC firms increased by more than 30% from 2000 to 2020[1]. Dividing this aggregate increase between VC firms investing in software and IT, and VC firms investing in other sectors, I show that the average increase in specialization is roughly 50% for software-focused VCs and 10% in other sectors. I posit that the increased specialization of the VC industry is primarily the result of technological advancements that led to reduced entry costs and a subsequent surge in the number of new startups in specific high-tech sectors. In fact, the average number of newly financed software startups in my sample increased by 44% since 2007. This created a more complex investment environment that requires more specific knowledge. I argue that specializing

[1]The increase is pervasive and obtains with different definitions of sectors, including a new measure that exploits the similarity of startups' business descriptions

can help VCs refine their search on a narrower set of similar startups within a larger pool and also better differentiate in an environment characterized by increasing competition from new VC funds.

To assess whether VCs' specialization is a response to reduced entry costs for startups in the software sector, I use the advent of Amazon's Web Services (AWS) in 2006. Ewens, Nanda, and Rhodes-Kropf, 2018 document that the advent of cloud computing[2] lowered the cost of initial investments in new software-related businesses. This enabled startups to scale up as demand grew, rather than making large fixed upfront investments in hardware. As a result it facilitated the entry of new startups into the software and IT sector by reducing the cost of entry. Lower entry costs increased the availability of software-related businesses, which in turn attracted new VCs, and increased the incentives to specialize in these areas, given the increased search costs associated with a larger pool of potential investments, and the need for VCs to differentiate from competitors. I find a significant increase in the probability of first-time investors financing software-related businesses following the introduction of cloud computing. In the years 2002-2005, less than 40% of VC firms made their initial investments in Software and IT startups. However, since 2006, this percentage has consistently risen, exceeding 70% in recent years.

In addition to receiving capital from new funds, my findings indicate that VCs also specialize more in treated sectors, aligning with the increased costs of search. I examine changes in VC firms' characteristics investing in different sectors before and after the AWS introduction and observe significant shifts. In Software and IT, the average VC firm becomes smaller and more specialized. VC market concentration in this sector decreases, and syndicate size grows. On the other hand, in *Deep Tech*[3] sectors, the average VC firm is now larger, the syndicate size decreases, and market concentration remains relatively stable. The influence of reduced early experimentation costs extends beyond new and young VCs. In a sample of larger VC firms that raise multiple funds, I show that the likelihood of these firms shifting their sector focus towards Software and IT nearly doubled after 2006. Remarkably, about 80% of VC firms in the sample never change their sector specialization, indicating sticky sectoral choices. I provide further evidence that the likelihood

[2] Cloud computing refers to the on-demand delivery of IT-related resources through the Internet, as opposed to an onsite server. https://www.startupguys.net/

[3] Although there is no unambiguous definition of *deep tech* or *tough tech* sectors, in this paper I follow the definition from https://mitsloan.mit.ed and identify these sectors as Biotech and Medical, Semiconductors, Industrial and Energy.

of changing industry focus decreases with higher VC specialization: a standard deviation increase in the VC firm specialization index is correlated with a 12% lower probability of changing industry, after controlling for factors like the VC firm age and size. This highlights the value of sector-specific knowledge in the VC context, emphasizing the importance of the initial industry choices, which can significantly impact subsequent investments.

To test the validity of these results in a different context, I test the same predictions in a subset of companies in Biotech following the introduction of CRISPR gene editing in 2012. CRISPR is a gene-editing tool that allows one to disable a gene or add DNA at precise locations in the genetic code. While it isn't the first gene-editing tool, it is believed to be a pivotal one that "has transformed labs around the world"[4]. It necessitates software tools and algorithms for efficient gene targeting, reducing experimentation costs, and making bio-informatics a key technology in molecular biology for genome editing (Nakamae and Bono, 2022). Results within the sample of biotech startups, where I define as *Treated* those related to software, IT, computer tools, genes, and DNA/RNA sequencing and editing, confirm the findings observed in Software and IT after the AWS shock: treated biotech startups receive funding from younger and more specialized VC firms, have a higher likelihood of attracting VCs' first-time investments, experience a decrease in market concentration, and an increase in syndicate size.

VCs make their specialization choices in time *t-1* and are more likely to choose sectors where they can more easily and quickly test the business viability of startups, focusing on thick markets that have abundant investment opportunities and a higher number of active VCs to benefit from larger networks. In aggregate, these individual decisions can lead to under-investment in thin markets, as VCs risk herding in sectors where they expect larger access to deal flow. *"No biotech ever really dies from dilution, they die from a lack of funding"* said a managing partner at William Blair during a recent interview, emphasizing the paramount importance of funding for startups. This underscores that, besides the impact on valuation and dilution, securing sufficient capital remains a critical factor for a startup's survival, and given the persistent investment behavior of VCs and the central roles of learning and networks in this setting, concerns regarding potential crowding-out effects due to specialization gain substantial relevance. Standard search models predict that an investor is more likely to meet an entrepreneur if the ratio of investors to entrepreneurs is low, while the entry of startups is increasing in

[4]https://spectrum.ieee.org/

that same ratio, as the entrepreneur is more likely to meet a venture capitalist in a given time interval if the ratio of venture capitalists to entrepreneurs is high (Inderst and Müller, 2004, Nanda and Rhodes-Kropf, 2017). This condition typically ensures that areas with higher VCs to startups ratio attract new VC entrants as the probability of securing a deal increases. However, in a market characterized by different technological risks across sectors, this condition may not hold, particularly when transitioning between sectors is costly. My sample of 25,409 entrepreneurial firms financed by 3,888 unique US-based VC investors, shows that since 2007, the number of both startups and VCs closing deals in software-related sectors has been constantly increasing, while it has decreased in Biotech (non-IT), Semiconductors, and Energy.

Another potential explanation of the sector shift documented in the paper is that non-software startups have undergone changes in recent years, possibly altering their characteristics in a way that no longer appeals to VCs. In this scenario, the observed reduction of non-software investments might be attributed to changes within these businesses and have little to do with changes in the software sector. To test this, I adopt a methodology similar to that employed by Hoberg and Prabhala, 2009, wherein I use a probit model and estimate the projected probabilities of investments in non-software startups while considering factors such as startup characteristics, investment and market conditions, and VC firms' characteristics. The estimation period is 2002 to 2007, and predictions are made for the period from 2008 to 2019. The average probability of non-software investments during the estimation period is approximately 55%. The actual probability drops to less than 30% in the period that goes from 2008 to 2019, with more than a 25% drop following 2007. When we consider changes in company characteristics, they account for approximately 5% of the decline in non-software investments. Additionally, considering market conditions, such as the book-to-market ratio of the startup industry, and the number of newly financed software startups from previous periods, explains an additional 10% of the reduction. However, a significant portion of this decrease in investment probabilities can be attributed to VC firms specializing in the software sector. The HHI of sector specialization of VC firms with a focus on software and IT almost bridges the gap between the actual and predicted probabilities of non-software investments, particularly in recent years.

A limitation of these findings is that VC investment databases reflect endogenous VC decisions, which prevent us from seeing the full universe of potential investments. To partially address this issue, I created a matched sample of non-VC-backed innovative young firms using USPTO patent data, considering factors like location, inventors count, years since the first patent, and patent technology classes (similar to Farre-Mensa, Hedge, and Ljungqvist, 2020, and Gonzalez-Uribe, 2020). While the share of new software-related businesses in the matched sample went from 33% of overall new innovative businesses in 2002 to 52% in 2018, the share of VCs in the same sector went from 18% to 75%. This suggests that the changes in VCs' industry choices are larger than changes in the underlying distribution of investment opportunities.

Finally, the existing literature suggests no conclusive evidence regarding the impact of specialization on VC firms' risk-adjusted performance (Gompers, Kovner, and Lerner, 2009). A recent report by Pitchbook indicates that the IRR of generalist and specialist funds is similar although in recent years, young specialist funds have outperformed young generalists (Hodgson, 2023). In the last part of the paper, I test how startups' outcomes relate to the technological shock and to VC specialization. First I show that for startups that receive financing in treated sectors post-shock, the failure rate is higher, even controlling for startups, VCs, and market characteristics. Second I show that a higher HHI of sector specialization is associated with higher IPOs and lower failures when looking at investments within the same industry and year. It remains unknown whether these effects result in higher or lower returns at the VC's portfolio level. Nonetheless, it is relevant to notice that these findings unveil higher experimentation in the treated sectors post-shock, and that specialization positively correlates with IPOs and with lower failures, suggesting a potential role of specialization in lowering information asymmetries in the market.

It is out of the scope of this paper to derive conclusions on whether the increased financing of software and IT technologies by VCs is good or bad. As Marc Andreessen explained in the famous piece "Why Software Is Eating the World"[5], there are many reasons to believe the development and diffusion of IT technologies will spur main innovations in all areas. This paper offers some guidance to understand how structural changes in the organization of innovation that disproportionately affect certain sectors impact the choices

[5] From Andreesen Horowitz webpage: https://a16z.com/why-software-is-eating-the-world/

of financial intermediaries that traditionally invest in innovation. While the important contribution of VC funding over the past decades led to regulations that increased capital deployed to these funds from other institutional investors, there are innovation areas that are proposing new financial structures and products, as their higher risk profile makes them unattractive to traditional VC investments (Fernandez, Stein, and Lo, 2012, Jack, 2023). Understanding how sector-specific technology cost and risk dynamics impact the evolution of private funding from investors like Venture Capitalists is key to assessing the financing of important innovation areas in the future.

The remainder of the paper is organized as follows. After a literature review in the next subsection, Section 1.2 lays out the conceptual framework of the paper, Section 2.2 describes the data, Section 1.4 starts by describing the observed increasing trend, and then uncovers the different potential channels underlying this trend, and Section 1.5 explores the consequences of entry and specialization choices. Section 1.7 concludes.

### 1.1.1 Related literature

The paper contributes to different strands of literature, and in particular to the literature on VC financing, and on the organization of financial intermediaries and innovation.

First, the paper directly relates to the study by Ewens, Nanda, and Rhodes-Kropf, 2018 on how technological shocks to the cost of starting new businesses have led the VC model to adapt. The authors document an increased prevalence of a *spray and pray* approach in recent years, and provide a framework that explains how this is happening in sectors where initial experiments significantly inform beliefs about the future potential of the startup. In this paper, using a longer time series. Additionally, I show that, by fostering thicker markets in certain sectors, this influences the specialization preferences of VC funds. As a result, it indirectly alters the VC market dynamics across various sectors. In a paper that also uses the introduction of AWS as a shock that spurred a boom in startup creations in certain sectors, Bonelli, 2023 studies the investments of VCs adopting data technologies. I also contribute to studies that uncover how VCs are involved in the choice of their sector specialization, by studying how changes in the cost of entry affect such choices. Evidence from (Gompers, Gornall, et al., 2020), suggests that VCs are actively involved in the decision of specializing vis-à-vis being a generalist, and there is large variation among different VCs: in the Gompers, Gornall, et al., 2020 sample of institutional VC firms, 61% specialize in a particular industry, and two industries stand out: 20% VC firms specialize in what can be broadly defined as the IT industry (including Software, IT, and Consumer Internet), 13% specialize in healthcare. Most VC firms in their sample invested in 3 or more industries, and a full 39% were generalists without an industry focus, but to date, the drivers of these specialization choices remain understudied.

Spaenjers and Steiner, 2023 find that sector specialization has increased also in the Private Equity (PE) industry over recent years, the authors find that specialists pursue targeted, hands-on value-creation strategies, and their results point to an equilibrium in which smaller specialists compete with larger generalists by leveraging industry-specific operating expertise in a chosen market niche. In this paper, I show that smaller and new funds are more specialized, and that lower entry costs in some sectors affect the choice of specialization. On the portfolio management of PE firms, a recent study by Brown, Fei, and Robinson, 2023 also discusses the trade-offs PEs face between focusing their skills and effort on fewer investments to earn higher returns, or investing more broadly to reduce risk through diversification. The authors show that these portfolio considerations are important for understanding fund-level private equity returns, and find that the largest investments in PE funds have the lowest returns on average but are also the least risky, and returns and risk are both increasing in industry or geographic concentration. While the existing literature suggests no conclusive evidence regarding the impact of specialization on VC firms' risk-adjusted performance, Gompers, Kovner, and Lerner, 2009 find a positive relationship between the degree of specialization by individual venture capitalists at a firm and its success. In this paper I also provide some evidence that specialization is positively correlated with lower failure and higher IPOs in a regression test with industry and year fixed effects.

Different theoretical papers study VCs' portfolio choices both at the individual level of a single VCs' portfolio and at the aggregate level. Fulghieri and Sevilir, 2009 investigate the optimal size and scope of a VC's portfolio and shows that the size and scope have a relevant impact on the incentives of both the VC and the entrepreneurs: a small portfolio impacts entrepreneurial incentives positively by reducing competition between start-ups for the VC's limited amount of resources. Moreover, VCs can benefit from portfolio focus, since larger relatedness between portfolio companies allows the VC to reallocate her resources and human capital more efficiently from one start-up to another and to extract more rents. Sorensen, 2008 consider the hypothesis that learning is important for VCs investment decisions as it allows VCs to resolve the uncertainties about technologies and investment opportunities. Aligned with this channel, I find that the probability that VCs change industry focus is decreasing in their specialization, also when controlling for VC firms characteristics and VC firm fixed effects. Outside the individual VC firm level, Hochberg, Mazzeo, and McDevitt, 2015 predict that in VC markets, the incremental effect of additional same-type competitors (specialists in the same sector) increases as the number of same-type competitors increases, which is a pattern that differs starkly from other industries, which typically show the incremental effects falling as the number of same-type competitors increases, and this is consistent with network effects that can soften competition. In line with the importance of networks, and specifically on the role of strategic alliances, Brinster and Tykvova, 2021 first provide evidence that alliances are more frequent among companies indirectly connected through VC syndication networks, then their results suggest that VCs' ties mitigate asymmetric information problems and that strategic alliances between companies from connected VCs' portfolios tend to perform well.

Inderst and Müller, 2004 develop an equilibrium model of contracting, bargaining, and search in which the relative scarcity of venture capital affects the bargaining power of entrepreneurs and venture capitalists. Michelacci and Suarez, 2004 also consider the theoretical linkages between the roles that the stock market and experts such as venture capitalists play in the financing of new ventures. In their models, a business is created when entrepreneurs and VCs get matched after a process of search. In equilibrium, the business creation rate is directly related to the number of entrepreneurs that search and the amount of capital available for funding them. These models do not consider different sectors within the VC industry, and in this paper, I provide empirical evidence that the sector choice of entry and specialization can act as a friction, and have significant implications on the amount of capital available for funding startups in different sectors. The concern of less financing devoted to startups outside the software sector is also raised by Lerner and Nanda, 2020, as they discuss how VCs are drawn to sectors in which this uncertainty can be reduced quickly. I argue that specialization can have unintended consequences such as crowding-out from specific technological sectors.

Outside of the PE/VC context, it has been shown that different financial intermediaries have been increasing their sector specialization in recent years. In a recent paper, Blickle, Parlatore, and Saunders, 2021 document that banks has become increasingly specialized by concentrating their lending disproportionately into one industry, and that this specialization improves a bank's industry-specific knowledge and allows it to offer generous loan terms to borrowers. Ben-David et al., 2022 show that ETFs providers are increasingly issuing specialized ETFs that track attention-grabbing themes. The authors propose that the dynamics of competition in the ETF industry fit the framework of Bordalo, Gennaioli, and Shleifer, 2015, where the authors model the behavior of suppliers in a market in which consumers have limited attention. To attract consumers, firms can make different product attributes salient. This paper contributes to this literature by showing how VCs are also choosing sector specialization to differentiate in an environment characterized by increasing competition from new VC funds, when they enter sectors with more VC activity. Jones, 2009 predicts that in a world with increasing *burden of knowledge*, innovators might compensate by lengthening their educational phases and narrowing their expertise, and this is why we see increasingly larger teams where each member can contribute to the team with very specific knowledge. The paper documents that in the cross-section VCs in sectors with higher technological risk are on average significantly more specialized than in other sectors. Finally, the paper contributes to the discussion that articles outside the economics and finance literature have on how changes in risk, technical, and capital requirements of different entrepreneurial projects affect the financing by private investors such as VCs (Fernandez, Stein, and Lo, 2012, Mitchell, 2009).

## 1.2 Framework and predictions

This section outlines the framework and predictions of the paper.

At an individual level, a venture capitalist's decision to specialize in a particular sector is essentially a portfolio management choice. When we consider this choice from the perspective of a new VC firm that lacks the resources and reputation of established VCs, I posit that they prefer sectors with specific characteristics. Namely, they prefer sectors where there are more investment opportunities available, where costs of experimentation are lower or the information about the startup's final value is revealed faster. As discussed in Ewens, Nanda, and Rhodes-Kropf, 2018, the advent of *cloud* *computing* allowed companies to rent scalable hardware in small increments, instead of making substantial upfront investments in physical infrastructure. This lowered the barrier to entry and led to a surge in new software-related businesses. Additionally, this technological advancement facilitated quicker and more cost-effective testing of the business viability of these startups. In this paper, I test these predictions using the introduction of *cloud computing* from Amazon Web Services (which was the first to market with a modern cloud infrastructure service), to show that after the introduction of cloud computing services, new VCs are indeed more likely to choose the software and IT sector for their first investments.

Following their initial sector choice, venture capitalists face the decision of whether to adopt a specialist or generalist approach. First, it is relevant to consider that the surge in the number of startups in specific sectors, increases the incentives for VCs investing in those sectors to specialize. The reason is that in thick markets searching for deals is costly, and differentiating from competing funds is important, especially for young funds. Search is costly because VCs need to screen among a larger pool of investment opportunities. Furthermore, reduced entry costs can enable worse entrepreneurs to enter the market, further increasing the cost of searching for attractive deals. This prediction implies that in markets that experienced a surge in investment opportunities due to lower entry costs and subsequent increase in VC entry, we should expect to see an increased degree of specialization, particularly among newer funds.

Besides the role of search costs, specialization choices are also driven by the choice of allocating scarce resources. The model by Fulghieri and Sevilir, 2009 predicts the optimal size of a VC's portfolio as a function of the expected payoff, the risk, and the sector focus of the portfolio companies, where the VC firm's capital allocation, also implies the allocation of its scarce human resources available. The trade-offs between a small and large portfolio, and its sector scope, are related to the entrepreneurial incentives as the investor can concentrate the human capital on a smaller number of start-ups, increasing the value-added services the VC firm can provide, and the possibility of the VC to better reallocate resources across portfolio companies in case of startup failure. This model implies that more established VCs with larger availability of capital and human resources are more likely to be generalists, as they can benefit from diversification but also have enough capital, experience, and knowledge to keep providing value-added services to their portfolio companies. Aligned with this prediction, in this paper, I find that increased specialization in software is indeed mostly driven by new VCs' entry.

Once the VC firms make their first investment choice, they start learning from those investments. Learning comes both from gaining private knowledge of past successes or failures in a specific sector (Sorensen, 2008), and also from knowing other investors, projects, and human capital in that sector. This last feature is particularly relevant for the VC positioning within the network. If learning from investments was indeed valuable, we would expect to observe that the likelihood of VCs investing outside their sector focus decreases as the level of specialization of the fund increases. In other words, the more specialized a VC fund is, the less likely they are to deviate from their chosen industry. I test this prediction in section 1.4.4, and find results consistent with this prediction. On top of this, some projects will have less uncertain payoffs and more immediate returns, while others will have more uncertain payoffs but greater potential to learn from them (Sorensen, 2008). In this case, we expect specialization to be more valuable where learning has greater value, and indeed I show that VCs are much less likely to deviate from their sector focus when they are specialized in sectors that entail high technology risk.

These individual choices made by VCs can have significant implications at the aggregate level. Existing literature on both the VC and banking industries, suggest that sector specializaiton can have relevant implications in terms of capital allocation: these intermediaries allocate more capital in sectors where they are specialized during turbulent times (Blickle, Parlatore, and Saunders, 2021, De Jonghe et al., 2019), and when public market signals are more favorable (De Jonghe et al., 2019). In a frictionless market, higher-risk investments would be compensated by higher returns, and VCs would naturally shift their capital from overfunded sectors to underfunded ones without the risk of crowding out. However, in a market with frictions, VC specialization could lead to crowding out effects. I will briefly discuss the main frictions within the VC industry that could lead to distortions in the optimal allocation of capital across different technological areas.

First, moving between sectors is costly, primarily because learning is valuable in this context. There are costs associated with deal sourcing, as the market is characterized by high information asymmetries which implies VCs need to spend a significant amount of time and resources screening potential deals. Furthermore, VCs often engage in post-investment value-added activities with their portfolio companies, and this process of learning is an important part of their value proposition. Importantly, learning in the VC industry extends beyond gaining specific knowledge about the risks and technologies of a sector. It also involves building relationships with other investors, as VCs usually participate in syndicated deals. The value of these networks can act as a friction that hinders VCs from easily transitioning between sectors, and it can make sectors where VC entry decreases less appealing as networks shrink. This is the "softened-competition" channel discussed in Hochberg, Mazzeo, and McDevitt, 2015, where the model predicts that in VC markets, the incremental effect of additional same-type competitors (specialists in the same sector) increases as the number of same-type competitors increases, which is a pattern that differs starkly from other industries.

In search models within the VC setting, a key variable is the ratio between the number of investors and the number of entrepreneurs. This ratio can be seen as an indicator of *informed capital scarcity*: the larger the number of searching entrepreneurs per investor, the slower an entrepreneur will find a suitable investor (Michelacci and Suarez, 2004, Inderst and Müller, 2004, Nanda and Rhodes-Kropf, 2017). This condition typically ensures that areas with fewer VCs attract new VC entrants as matching probabilities increase. However, earlier we discussed the idea that competition could be partially mitigated by the advantages offered by networks. Furthermore, lower VC entry in a sector also poses an increased risk for startups in underfunded sectors of not securing sufficient financing. This implies that expected returns from investing in a sector receiving relatively less financing should also account for the increased risk of startup failure due to limited available funding. Considering that sectors with relatively less VC entry in recent years often involve high-risk technologies, risk adjustment through valuations might not be enough to attract the capital needed.

Finally, increased VC entry in sectors with faster intermediate outcomes can create pressure on VCs that opt for sectors involving the financing of more complex technologies, where information is revealed more slowly. From the perspective of Limited Partners (LPs) who invest in VC funds, this choice may be perceived as overly risky or less promising. As a result, LPs might withdraw their investments from those VCs making investment choices that deviate from the industry average.

The presence of these frictions can result in suboptimal capital allocation in the VC industry, where VCs may remain concentrated in overfunded sectors and underserve promising startups in underfunded areas. To empirically test this prediction one would ideally require access to a comprehensive dataset including the entire spectrum of investment opportunities available to VCs. However, commonly used datasets like VentureXpert only provide information about startups that successfully secured VC financing. To the best of my abilities, I provide evidence that the large shift toward software does not appear to be justified by likewise changes in the distribution of new innovative businesses, and of startups' characteristics. Further exploration and improvements of this part are at the top of my research agenda.

## 1.3 Data

### 1.3.1 VC Data

The paper's starting point is the universe of transactions made between January 1980 to December 2022 that are registered in Securities Data Company's (SDC's) VentureXpert database. VentureXpert is considered one of the most comprehensive datasets about VC investments and it provides information on rounds, investors and portfolio companies. I focus on investment rounds made by U.S.-based investors, and to restrict my analysis to VC deals, I restrict the sample to investments made by funds whose investment type is identified as "Venture Capital". I then exclude deals where VC or company information is missing, or where the amount invested in each round is missing. For data completeness, the main analysis is conducted on the sample of early-stage investments made from 2002 up to 2019. I conduct the main analysis at the VC firm level, as existing literature has documented that exchange of information happens also at the firm level Gonzalez-Uribe, 2020, as well as main investment decisions. It is worth noting that when moving from the firm to the fund level, many observations are lost for those funds identified as "unspecified fund", while the investments of these unspecified funds can be used when we analyze the data at the firm level. The final sample includes 25,409 entrepreneurial firms financed by 3,888 unique US-based VC investors. The main sample has 118,132 observations at the investor-startup-investment date level of financing. Table 2.1 provides summary statistics of the main variables used in the analysis. Panel A contains deal characteristics at the VC-firm level, Panel B describes characteristics at the portfolio company level. To cluster start-ups in more meaningful industry clusters than the one provided by VentureXpert, I start from the industry classification based on 10 different industries in VentureXpert, and then aggregate them in 6 different groups based on their similarity of innovation. The 6 groups obtained are Biotech and Medical with 4,392 startups (17.3%), Communications and Consumers with 2,021 startups (8%), Hardware and Semiconductors with 1,968 startups (7.6%), Industrial and Energy with 972 startups (3.8%), Software and IT 14,672 startups (57.7%), and *Others* (1,384 startups). Gompers, Kovner, and Lerner, 2009 also use a 9-industry classification from VentureXpert for computing the HHI of VC firms and funds, and Ewens, Nanda, and Rhodes-Kropf, 2018 use 5-industry groups from Pitchbook. Although any industry classification is to some extent arbitrary, I believe the 6 industries classification scheme outlined in Panel C of Table 2.1 and **??**, captures businesses that have similarities in technology and management expertise that would make specialization in such industries meaningful.

### 1.3.2 Innovation Data

I gather innovation data using patent applications filed at the US Patent Office (USPTO) and retrieved through PatentsView. I match this dataset with VentureXpert to identify VC-backed patents. To merge the datasets, I follow a similar procedure to Bernstein, Giroud, and Townsend, 2016. I start by matching each standardized name of a company in VentureXpert with standardized names from the USPTO dataset: if an exact match is found, this is taken to be the same company and removed from the list. For the remaining companies, I use a fuzzy matching technique that gives a similarity score of stem names. If a similarity score higher or equal to 90% is found I combine this information with other identifying information, such as founding dates, patents grant dates, and headquarters' city. Furthermore, as I want to identify innovations in the portfolios of VC and not all innovations belonging to companies funded by VCs many years before, I restrict the VC-backed patents sample to patents filed within 10 years since the company received financing from the VC. Of my main sample of 25,409 international startups, I identify 9,900 startups that have at least one patent granted by the USPTO, the share of patenting start-ups compared to the overall sample of startups is in line with other papers matching these two datasets. To measure reliance on science, I get the data provided by Marx and Fuegi, 2020, which identifies citations that a patent makes to scientific papers.[6]

## 1.4 The analysis

### 1.4.1 Specialization trend

The VC market increased significantly over the past years. The number of deals in the United States went from less than 3,000 in 2004 to more than 13 thousand a year since 2019[7]. I document that this increase goes along an increased sectoral specialization of VCs in recent years. I compute the specialization of a VC firm as a Herfindahl-Hirschman Index (HHI) of concentration of capital invested across different industries by a VC Firm at the investment date:

$$Specialization_i = \sum_{j}^{n_i} s_{ij}^2 \tag{1.1}$$

Where $s_i^2 j$ denotes the percentage of the amount invested by Firm $i$ to industry $j$, out of $n_i$ industries, and the sum is the Herfindahl concentration index. Thus, if a VC firm invests all its capital in one sector, its index will be equal to 1, while it will get closer to zero as capital is more equally spread across different industries. One alternative way to compute this measure is by using the number of companies the VC firm invests in across industries, rather than the amounts the VC invests. While the trend is robust also using that alternative specification, it seems more reasonable to consider the dollar amount invested by a fund in a company as a measure of where the VC has more skin in the game, being these investments equity investments.

This measure is sensitive to the type of industry classification one uses, but the trend is robust to different specifications[8]. The 6 sectors used in the main analysis are Biotech and Medical, Communications and Consumers, Hardware and Semiconductors, Industrial and Energy, Software and IT, and Others. While six sectors may seem a not granular enough classification, it is important to notice that these financial intermediaries invest in a relatively

[6] The authors link data from the USPTO to a broad set of scientific articles not limited by industry or field. Their algorithm can capture up to 93% of patent citations to science with an accuracy rate of 99% or higher.

[7] From The NVCA Yearbook 2023:https://nvca.org/

[8] Figure **??**, plots the same results as in Figure 1.1 but with text-based sector classification that allows for more granular clustering. The text-based industries obtained with the text-based computation are outlined in Table **??**.

small number of companies that have very specific businesses, mostly high-tech, so classifications that try to map the same granularity as in public markets might not be able to capture the similarities in startups' technologies. Although any industry classification is to some extent arbitrary, I believe this classification scheme captures businesses that have similarities that would make specialization in such industries meaningful.

As the index is also sensitive to the number of companies the fund invests in, I either control for the number of investments made by a VC (in the regression tests), or use an HHI that is adjusted for the number of investments the VC firm made (in the figures), in order to control for the effects of the investment by first-time funds. The adjustment follows the methodology in Hall, Jaffe, and Trajtenberg, 2001, that discounts the index by the (inverse of) the number of companies the fund invested in (e.g., if the fund only invested in 3 companies, all in the same industry, its HHI will not be equal to 1 but to $2/3$, which is obtained by multiplying it by $(n-1)/n$ companies), or I control for the number of investments made by the VC firm.

Results are reported in Figure 1.1. To provide a numerical example of what the average indexes reported in panel A of Figure 1.1 mean, consider a fund that decides to allocate 10 USD in two different industries: a typical fund at the beginning of this century would allocate approximately 5 dollars in each industry, an average VC firm two decades later would allocate approximately 8 dollars in an industry and 2 in the other. Interpretation of Panel B of 1.1, instead tells us that until 2006-07 in a syndicated deal there used to be on average slightly more than half funds in the same focus industry as the focal start-up, 10 years later the average syndicated deal has more than two-thirds of the funds in the same focus industry of the focal start-up. This is not a mechanical effect of the average syndicate becoming smaller, indeed the syndicate size even increased over the years. It is interesting to notice that while syndicate size and VC specialization are positively correlated, suggesting that funds can make up for their narrower focus by co-investing with more funds, which is similar to what happens at the level of inventor teams, as documented in Jones, 2009, the fact that funds co-invest more and more with other funds in their focus industry suggest VC networks are also becoming more specialized, which in turns increases the incentives to higher specialization.

VC funds usually have a life span of 8-10 years during which they invest in the portfolio companies in multiple rounds of financing (the so-called staged financing) before exiting their investments. As follow-up rounds of financing mainly depend on the probability of the startup proving its success at different stages, the specialization choices of a fund are usually made by the first investments the VC makes in each new portfolio company during the first years of the fund's activity. I therefore also analyze the specialization of each VC firm (and fund) by its first portfolio companies' investments during the first 5 years since the VC was founded. Figure **??** plots the coefficients of an OLS regression where the dependent variable is the adjusted HHI, and it is regressed onto time dummies at the year level where 1980-1994 are the reference years. The timeline stops in 2015 as a full-time series of 5 years is needed to compute the index at the vintage year.

Provided that VCs are choosing to be increasingly more specialized over recent years, what is driving their industry choice of specialization? What types of VCs are becoming more specialized and in which sector? The next section will start by addressing VC firms' initial sectoral choice.

### 1.4.2 VCs' initial sector choice

In a setting where learning and networks are valuable, the initial sector choice of a VC is important as this can in turn affect subsequent investments. VCs that do not have much experience or a renowned name can find it optimal to choose as first investments technological areas that can deliver faster outcomes and where the initial funding required is smaller. I test this hypothesis by using the advent of cloud computing as a shock that significantly impacted the cost of experimentation in the software industry.

In 2006, Amazon Web Services (AWS) started offering IT infrastructure services to businesses as web services (now known as *cloud computing*). One of the benefits of cloud computing is the opportunity to replace upfront capital infrastructure costs with low variable costs that scale with the business. This shock significantly decreased the cost for potential new startups to start a business in Software and IT. This affected the type of financing software-related startups needed, as Ewens, Nanda, and Rhodes-Kropf, 2018 show that treated startups raised significantly smaller amounts in their first round of VC financing. In turn, it affected the number of new start-ups that could be created in this sector as the cost of starting a business in this sector decreased significantly[9]. In fact, the average number of newly financed software startups in my sample increased by 44% since 2007.

[9]This can also have important implications for founder-CEO who decides to start a new business (Ewens, Nanda, and Stanton, 2023)

Furthermore, to test the validity of a shock in the costs of entry and experimentation in a different context, I also use the introduction of CRISPR gene editing in 2012 for the biotech sector. CRISPR is a gene-editing tool that allows one to disable a gene or add DNA at precise locations in the genetic code. While it was not the first gene-editing tool, it is believed to be a pivotal one. It necessitates software tools and algorithms for efficient gene targeting, reducing experimentation costs, and making bio-informatics a key technology in molecular biology for genome editing (Nakamae and Bono, 2022). For biotech startups, I define as *Treated* those related to software, IT, computer tools, genes, and DNA/RNA sequencing and editing.

Table 1.2 reports the results of a t-test for differences in mean of time to exit, days to second round, and initial amount invested. AWS-treated companies are identified using portfolio companies names or descriptions having at least one of the words "Online", "E-commerce", "Hosting", or "Web" in each industry segment. Results show that software-treated companies report significantly lower years to exit, and lower initial amount invested compared to non-treated companies. In the sample of biotech companies, treated ones do not report faster exit time in the sample, but they do show a significantly lower initial amount invested compared to non-treated biotech companies. Table **??** focuses instead on testing the mean time to exit and to receive a second round, and the average amount received and share of new VCs, in the 2004 and 2005 for the pre-period and 2006-2007 for the post-AWS period. The results report the t-tests for differences in means for variables describing the characteristics of software versus non-software investments. There has been a significant change in software investments relative to non-software after the introduction of AWS, in line with Ewens, Nanda, and Rhodes-Kropf, 2018 findings. In the main analysis, the main estimation strategy is a standard differences-in-differences regression, where the main coefficient of interest is the interaction between *Treated* startups as defined above, and a *Post* dummy that takes the value of one for investments after 2006 (for the AWS shock), and after 2013 (for CRISPR).

In table 1.3, I test the probability that the investment in a software-related company is the first investment of a new VC. The table reports the results of a linear probability model [10] where the dependent variable takes the value of 1 if the investment in the startup is the first investment ever by a VC firm. In column 1 *Treated* includes all companies in the software and IT sector, while

[10]For ease of interpretation the main text reports results of the OLS regression, but results are robust to specifications with both a logit or probit model.

columns 2 and 3 use the more granular classification of software-related startups using companies' business descriptions, which allows me to include industry fixed effects (Column 3).

We can see that when the costs of experimenting in the affected industry decrease (after 2006), an investment in a treated startup is 0.7% more likely to be a first-VC firm investment. The regression includes a large set of controls (i.e., the natural logarithm of the round's syndicate size, dummies for entrepreneurial companies' headquarters state, as well as quarterly lagged measure of the median of the yearly book-to-market ratio of all public companies in the same sic2 industry, and a lagged measure of the number of IPOs and M&As). To better understand the relevance of these findings from the investors' side, Figure 1.2 shows how the share of first investments by new VCs has changed over the years. Less than 40% of VCs in the pre-period between 2002 and 2005 made their first investments in software, while that share increased to up to approximately 70% in 2015-2019. Table 1.7 shows that also for biotech, treated startups after the introduction of the CRISPR tool experience a 1.1% higher probability of receiving investments from first-time VCs.

### 1.4.3 In which sectors are VCs specializing?

Jones, 2009 discusses the possibility that if innovation increases the stock of knowledge, then the educational burden on future innovators may increase. To make up for this increased difficulty, innovators might compensate by narrowing their expertise. It is therefore reasonable to believe that in a world with an increasing "burden of knowledge", hands-on investors such as VCs, might need to narrow their expertise by reducing their investment focus to fewer sectors to keep being at the frontier of innovation. Furthermore, if specialization helps mitigate difficulty, we should see overall higher specialization in fields where more technical knowledge is required: as Jones, 2009 shows, the age at first invention, specialization, and teamwork increase over time in a large micro-data set of inventors, and in the cross-section, specialization and teamwork appear greater in deeper areas of knowledge.

Figure 1.3 reports a monthly time series of the average specialization index of VC firms, where VC firms are divided according to their sector focus. The sector focus is computed by considering which sector has the largest amount of dollars invested by the VC firm to that date. As an example, the chart reports that at the beginning of 2008, VC firms in *Deep Tech* areas[11], had on average a specialization index higher than 0.55, and that index grew to more than 0.6 since 2016 (a 0.6 index, in the case of a VC that invested 10USD in two industries, means having 7USD in one industry and 3USD in the other one). Aligned with the idea of higher specialization following higher technical knowledge, the figure shows that there are differences in the HHI levels depending on the VC firm industry focus. At the same time, we can see how the change in the historical trend, appears to be mostly driven by Software and IT: the average index for Software-focused VCs was approximately 0.4 in 2007, and grew to 0.6 since then, which represents a 50% increase.

I posit that this increased specialization is mainly the result of technological advancements that led to reduced entry costs and a subsequent surge in the number of new startups in specific high-tech sectors. To assess whether VCs' specialization is a response to reduced entry costs for startups in the software sector, I use the advent of Amazon's Web Services (AWS) in 2006, and of CRISPR in 2013, as described in Subsection 1.4.2, in a standard difference-in-differences estimation. Table 1.4 reports the coefficients of an OLS regression where the dependent variable is the natural logarithm of the VC firm's specialization index at the investment date. Observations are at the company-VC firm first investment level and in all specifications, controls include the headquarters location of the startup, as well as a dummy if the startup is located in an entrepreneurial hub, and quarterly lagged measure of the median of the yearly book-to-market ratio of all public companies in the same SIC2 industry. The main coefficient of interest, *Treated X Post* is positive and significant in all specifications. After treatment, software-related investments experience a 4.4% increase in investor specialization (and 9.5% within biotech after CRISPR). It is worth noting that Columns 2 and 4 of the table also report the index is computed using the most granular industry

[11] I look at two indicators of the technical risk and knowledge, and reliance on science needed across the different startups' sectors in the sample: intellectual property (IP) intensity, measured as the average number of patents issued by a startup in that industry (where startups that issue zero patents are included in the denominator. An alternative could be to only compute the average among those startups that issue at least one patent, while the resulting average would be much different (i.e., larger), the different ranking industries by this measure would be the same.), and citations to scientific articles made by startups' patents. Table **??** shows that there are relevant differences in these measures across different industries, with sectors such as Biotech having the highest number of citations to academic articles compared to innovation issued in other industries. At the same time, as expected the software and IT industry, is the one with the lowest IP intensity as much of the innovation issued by software and internet startups cannot be patented. In the remainder of the paper I will often refer to *tough tech* startups as startups in industries such as Biotech, Industrial and Energy, Hardware and Semiconductors, as opposed to *soft tech* startups that are the ones in software and IT and communications.

classification available, which includes more than 500 sectors and considers different end-uses of the startups' technologies. Yet, even with that classification, investments' specialization increases for treated startups, suggesting that VCs might also be narrowing their focus to fewer segments within larger sectors after treatment.

### 1.4.4 Deviating from specialized investments

Learning is valuable for VCs as young entrepreneurial projects are characterized by high uncertainty about technologies (Sorensen, 2008). For this reason, we might expect a VC firm to be less likely to invest in an industry outside its focus industry the more that VC firm becomes specialized. This is what results in Table 1.5 show. The table reports the coefficients' results of the following OLS regression [12] specification:

$$Pr(Change\ Industry)_{i,t} = \beta_1\ VC\ Specialization_{i,t-1} + X'\theta + \omega_t + \phi_i + \gamma_k + \epsilon_{i,t} \tag{1.2}$$

The dependent variable is 1 if the VC invests in a sector that is outside its focus at time $t$, and this is regressed onto the VC's standardized HHI of sector specialization in $t-1$, the natural logarithm of the VC firm age and the natural logarithm of the VC's amount invested up to that date are used as controls, on top of controls of startups characteristics and market conditions, $\omega_t$ includes investment year fixed effects, $\phi_i$ VC firm fixed effects, and $\gamma_k$ industry fixed effects.

Column 1 shows that in the cross-section, a standard deviation increase in the VC-firm's HHI of sector specialization in *t-1*, decreases the likelihood of changing industry in time *t* by 12% with a 95% confidence interval. Moving to column 2 where I add VC firm fixed effects, we see that results are robust also within VC, where a standard deviation increase in the HHI corresponds to a decrease in the probability of investing outside the industry focus by 3.7%. These results are aligned with a setting where specialization and learning are valuable, and might be different from results we would expect in a standard setting with portfolio risk diversification. Finally, in line with learning being more valuable in industries that require more technical knowledge, results in columns (3) and (4) focus on the subset of VC firms whose investment focus is in *deep tech* industries or software and IT, respectively. The results show that within the subset of firms with an industry focus in *deep tech* industries, a one standard deviation increase in the HHI of sector

[12] For ease of interpretation the main text reports results of the OLS regression, but results are robust to specifications with both a logit or probit model.

specialization is associated with an 18% lower probability to change sector at a 99% confidence level, while within the subset of firms with a sector focus in *software and IT* the decrease is of 12% and significant at a 95% confidence level. The difference in coefficients in columns 4 and 5 suggests there might be a different degree of relevance in learning between *deeptech* and software investments.

Finally, Figure 1.4 focuses instead on a sample of larger VC firms that raise multiple funds. The analysis identifies VC firms' focus based on the sector focus of each fund, defined by the largest amount invested by the fund across different industries. Figure 1.4 reports in Panel A, the share of VC firms shifting their industry focus towards Software and IT (in blue), and away from Software and IT (in red). The change is identified when a subsequent fund raised by the VC firm has a sector focus different from the previous funds raised by the same VC. We can see that the share of VC firms that raised a new fund in Software and IT even if that was not their industry focus, more than doubled from 2006 to 2014, uncovering the fact that entry in the Software and IT space was not limited to new VCs, and also incentivized some of the large existing ones to enter that sector. Panel B reports the share of new funds raised by the VC firms that remain in the same focus industry and unveils the persistence of sector-specific VC investments which we investigate further in the next subsection.

### 1.4.5 Heterogeneity of VC firms

In this section, I explore changes in VC firms beyond VC firms' specialization. If the entry of new VCs increases in treated sectors, we expect the average VC firm age and size to decrease in such sectors after the shock. At the same time market concentration should also decrease and the size of syndicated deals, in terms of the number of VCs co-investing in a deal might increase following more entry. Furthermore, I test how these characteristics changed for non-software startups. In 1.6, I focus on the differences in the average VC firm characteristics in Biotech & Medical versus Software & IT, after the introduction of cloud computing in 2006. The reason for this comparison is motivated by the fact that Biotech and Software are the two main sectors in which VC firms invest (see the distribution of deals in Table 2.1), and even though Biotech was also impacted by the introduction of cloud computing (as any industry), the average intensity of treatment was much lower within the whole industry, and confined to software-related biotech companies. The main shock for such companies though was represented by the introduction of tools such as CRISPR, and indeed this sector-specific shock will be analyzed in Table 1.7.

Table 1.6 shows that after the advent of cloud computing, the average VC firm investing in Biotech & Medical is 8.8% older, 37.1% larger, and the syndicate size of the average investment decreases by 7.4%. At the same time, while the specialization of the average VC firm is on average 10.5% higher for Biotech companies, it hasn't increased in the post-period. Businesses in the Software and IT sector instead, after the introduction of AWS, experienced a 1.3% increase in the HHI of the average VC firm, and a 10.2% increase in the average round syndicate size (measured as the number of VC funds co-investing in an investment round). Furthermore, an important result is reported in column 4, where the dependent variable is the market share of a VC firm in the industry and year-quarter of investment. The market share of a VC firm in the post-period, decreased in the software and IT sector by 1.3%, which is consistent with increased entry of new VCs in this sector.

Table 1.7 tests the same changes in characteristics as in Table 1.6 in the subset of biotech and medical companies. In this setting, treated companies are those operating in the biotech industry whose business is related to gene editing and sequencing, biotech software, or bioinformatics. Post is a dummy that equals one if the investment year is after 2013 (CRISPR introduction). As explained also in subsection 1.4.2, the idea is that treated companies benefited from lower costs and lower time of experimentation when the gene-editing tool CRISPR was introduced, as shown in Table 1.2, and software-biotech became key to the success of this technology. Columns 1 and 2 show that treated-biotech businesses receive financing from VC firms that are on average 16.6% younger and 25.7% smaller compared to non-treated companies in biotech after CRISPR technology advancements. Treated companies also report a 1.3% decrease in the average industry-quarter market share, probably due to new VCs entering this technological area, and indeed in Column 6, we see that the probability that treated companies receive a first round by a new VC increases post-treatment. In this case too, the number of VCs co-investing in a round significantly increased by 10.3%.

Overall, these results suggest that the increased entry and specialization in software-related businesses have led to significant changes in the average VC firm financing this sector, both compared to their previous state and to VC firms in other sectors. Additionally, a noteworthy change is observed in the average VC firm financing biotech companies, where VCs become notably larger and older, pointing towards reduced entry into the sector and a more prominent role played by well-established investors. These findings raise questions about the implications of these changes on startups. On one hand, one could argue that the financing of highly technical sectors by larger and more experienced VC firms is an optimal outcome, as older and larger VCs may bring more capital and expertise to sectors that require substantial resources and knowledge. This may enhance the ability to bring innovative products to market. Conversely, if these changes are not primarily driven by efficiency but rather stem from reduced participation in non-software sectors, it may raise concerns, as this implies a potential risk of under-investment in some technological areas, which could hinder their growth and innovation.

## 1.5 Implications for non-software startups

So far we saw that VC firms have been narrowing their investment focus to fewer sectors over the past years. I tested the hypothesis that technology shocks to entry costs can lead to new VCs and increased specialization in innovation areas that benefited from the shock. Absent any friction, these individual choices made by VCs would not raise concerns of potential underfunding of non-software sectors, as higher-risk sectors would be compensated by higher returns, and VCs would naturally shift their capital from overfunded sectors to underfunded ones without the risk of crowding out. But as discussed in section 1.2, moving between sectors is costly, as learning is valuable in this context. Learning in the VC industry extends beyond gaining specific knowledge about the risks and technologies of a sector, and also involves building relationships with other investors, as VCs usually participate in syndicated deals. The value of these networks can act as a friction that hinders VCs from easily transitioning between sectors, and it can make sectors where VC entry decreases less appealing. Furthermore, lower VC entry in a sector also poses an increased risk for startups in underfunded sectors of not securing sufficient financing.

My sample of 25,409 entrepreneurial firms financed by 3,888 unique US-based VC investors, shows that since 2007, the number of startups and VCs closing deals in software-related sectors has been constantly increasing, while it has decreased in Biotech (non-IT), Semiconductors, and Energy. Figure 1.5 reports the number of active unique startups and VCs within a sector and quarter. The figure shows that the trend in the number of VCs and startups was similar, and increasing, across the four different sectors up to 2007-2008, but then, while it kept increasing for software-related sectors, it started decreasing for non-software, where the number of different VCs is the first to drop, followed by the number of distinct startups.

### 1.5.1 Probability of non-software investments

An alternative explanation of the sector shift documented in the paper is that non-software startups have changed in recent years, perhaps altering their characteristics in a way that no longer attracts VCs. In this scenario, the observed decline in non-software investments may be attributed to shifts within these businesses rather than changes in the software sector. To investigate this, I adopt a methodology similar to the one employed by Hoberg and Prabhala, 2009, to estimate the projected probabilities of investments in non-software startups, accounting for factors such as startup characteristics, investment and market conditions, and VC firm characteristics.

Figure 1.7 illustrates the dynamics of actual and predicted probabilities of non-software investments. The estimation period covers the years from 2002 to 2007, and I use a probit model to estimate the projected probabilities for the 2008-2019 period, with the dependent variable taking the value of 1 if the investment is in a non-software business. During the estimation period, the average probability of non-software investments stands at approximately 55%. However, there is a significant drop in the actual probability, which falls to less than 30% after 2007 and remains lower than 30% for the whole period, up to 2019. This decline represents a reduction of more than 25% following the year 2007. When examining the factors contributing to this decrease, I first consider changes in company characteristics and include in the probit regression the age of the startup, the state location, whether it is located in an entrepreneurial hub, and whether the startup issued patents. Adding company characteristics accounts for approximately 5% of the decline in non-software investments, as shown by the red line in the graph, which suggests that there were indeed changes in the average startup in non-software, but these changes only explain a small share of the overall trend. I then consider market conditions, including the book-to-market ratio of the startup industry and the number of newly financed software startups in the previous quarter, which explains an additional 10% of the actual reduction.

Notably, it seems that a substantial portion of this decrease in non-software investment probabilities can be attributed to VC firms that specialize in the software sector. The HHI of VC firms with a focus on software and IT plays a significant role in bridging the gap between the actual and predicted probabilities of non-software investments, particularly in recent years. This suggests that the specialization of VC firms in the software sector might be an important factor influencing the observed changes in investment patterns.

### 1.5.2 Evidence from a matched sample

The paper documents that there has been a significant decrease in new funds entering non-software sectors compared to software-related ones. A quote from a managing partner of a renowned VC firm, which says that *"No biotech ever really dies from dilution, they die from a lack of funding"*, emphasizes the paramount importance for startups to secure sufficient funding. Securing funding remains the most critical factor for any startup's survival, and given the persistent investment behavior of VCs, and the central roles of learning and networks in this setting, concerns about potential crowding-out gain substantial relevance.

A limitation of my findings is that VC investment databases reflect endogenous VC decisions, which prevent us from seeing the full universe of potential investments and only show us the result of matching. It could be the case that the decrease in the supply of VC funding in non-software simply follows a decrease in the supply of startups in these sectors. To better understand these potential dynamics at the VC-backed and non-VC-backed startups, I created a matched sample of non-VC-backed innovative young firms using USPTO patent data. Similar to Farre-Mensa, Hedge, and Ljungqvist, 2020 and Gonzalez-Uribe, 2020, I consider factors like location, inventor count, years since the first patent, and patent technology classes. Namely, from the USPTO database, I first keep only patent assignees that are marked as US private companies, I keep those located in California, Massachusetts, Texas, and New York, which are areas that make up more than 70% of deals in the VentureXpert database. I then only include companies that issued no more than 50 patents and have no more than 15 inventors, following the distribution of the number of patents and number of inventors in the VC-backed sample of patenting startups (99% of VC-backed patenting startups issue less than 50 patents, and have less than 15 inventors on average). I then keep only companies that issue their patents within 10 years since the first one. Finally, I keep the most frequent patent classes for the four sector groups reported in Figure 1.5. I ended up with a sample of 39,497 patenting companies, of which 3,735 are VC-backed, which represents a 9.4%, in line with the matched sample obtained by Farre-Mensa, Hedge, and Ljungqvist, 2020.

Figure 1.8, Panel A, reports the distribution of the number of startups from 2002 to 2018, by sector. We can see that, while the share of new software-related businesses in the matched sample went from 33% of overall new innovative businesses in 2002 to 52% in 2018, while for the semiconductors and energy sector, the share decreased from 45% in 2002 to 27% in 2018, suggesting that a relative decrease in startups in some areas can be at play in determining the relative scarce presence of VCs. Nonetheless, if we shift our focus to Panel B, we can see that the share of VCs in software went from 18% to 75% in 2018, and the share in the semiconductors and energy sector from 42% to 11%, showing a much larger change in the distribution of VCs across sectors than that of startups supply. It is also worth noting that while the share of software-biotech businesses remained quite stable, the share of VCs in that area almost doubled and happened around 2013, coinciding with the introduction of the new gene editing tools. This evidence suggests that the changes in VCs' sector choices are much larger than the distribution change in the number of investment opportunities, and might be linked to the reduced cost of experimentation in affected sectors.

## 1.6 Startups' exit

In this last section, I explore the potential implications of this sector-specific shock for startups' exit. The existing literature suggests no conclusive evidence on the impact of sector specialization on VC firms' risk-adjusted performance. Pitchbook recently released a report that shows how the IRR of generalist and specialist funds is similar although in recent years, young specialist funds have outperformed young generalists (Hodgson, 2023).

Table 1.8 reports the results of a linear probability model where the dependent variables are equal to one if the startup exited through IPO or M&A within the 10 years following its first financing, or if the startup failed[13]. In the first 3 columns, I test the probability of exit or failure for treated startups in the post period, where *Treated* refers to portfolio companies whose description has at least one of the keywords "Online", "E-commerce", "Hosting",

[13] *Failure* is identified using the variable *Defunct* in VentureXpert. An alternative way was to identify as failed startups that did not appear in the dataset after the first financing rounds and did not register an exit, but this entails the risk of including startups that simply remained private and did not receive further VC financing.

or "Web", and *Post* refers to whether the startup received the first financing by the VC firm in the period following the introduction of AWS. The results show a lower probability of M&A and a higher probability of failure, for treated startups in the post period. This is consistent with results and predictions discussed in Ewens, Nanda, and Rhodes-Kropf, 2018, that the reduced cost of starting businesses in treated sectors made abandonment options more valuable.

In the last 3 columns of Figure 1.8, I test the probability of exit or failure on the standardized HHI (standardized by removing the mean and dividing it by the standard deviation) of VC-firm $i$ that invested for the first time in company $j$ at time $t$. This regression includes *Industry X Year* fixed effects, to explore differences in the cross-section of VC firms' HHIs within the same sector and year. Results show that a 1 standard deviation increase in the VC's specialization index is correlated with a 0.5% higher likelihood of selecting a business that will exit via IPO and a 1% lower likelihood of failure. Although these results suggest a positive correlation between the quality of startups and the specialization of a VC firm, it is important to consider that the unconditional probability of failure surpasses that of IPOs, so these results do not tell us if these effects result in higher or lower returns at the VC's portfolio level, but suggest a potential role of specialization in mitigating information asymmetries.

## 1.7 Conclusions

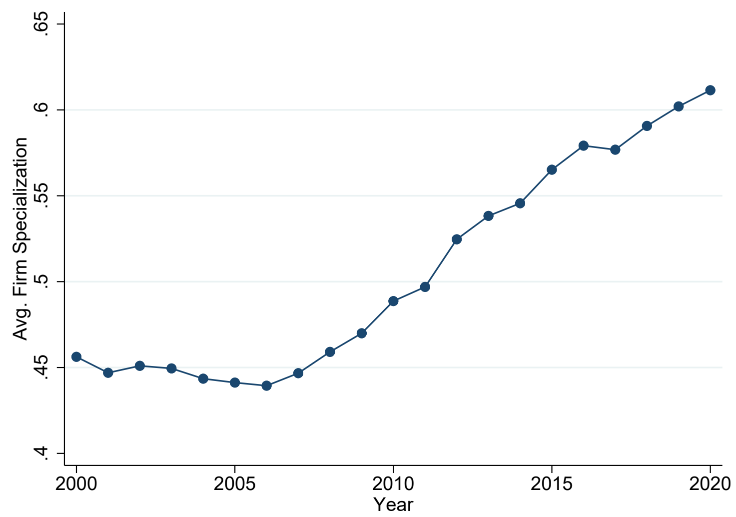
This paper explores the determinants of VCs sector specialization choice, its evolution over time, and its impact on startups. I document a significant increase in sector specialization among US-based VC firms in recent years, and posit that this shift is the result of technological shocks to the initial cost of starting new businesses in specific sectors. The introduction of technologies like Amazon's Web Services (AWS), by lowering entry costs, increased the number of investment opportunities and this had an impact on VCs' sector choices and specialization. First, specializing can help VCs refine their search on a narrower set of similar startups within a larger pool and also better differentiate in an environment characterized by increasing competition from new VC funds. Secondly, faster access to business viability in software-related startups attracted new, young VCs, leading to increased specialization as young and smaller funds tend to have a narrower sector-focus. Less than 40% of new VC firms used to invest in Software and IT before 2005, and the share went up to almost 70% in 2015-2019. As sector-specific knowledge is valuable, the probability of changing industry focus is decreasing in the VCs' sector specialization, which implies that the initial industry choice by a VC has a lasting impact on subsequent investments.

While specialization has advantages in terms of narrowing search and reducing information asymmetries, in aggregate, it may also lead to crowding out in certain sectors. I highlight significant changes in VC investment behavior across different sectors following the shocks, where non-software startups remain the domain of larger established VC firms, and experienced a drop in VC activity, compared to the software sector. This suggests that at the aggregate level, the increased specialization of VCs in certain sectors can have implications for the dynamics of startups' financing. The paper offers some guidance to understand how structural changes in the organization of innovation that disproportionately affect certain sectors impact the choices of financial intermediaries that traditionally invest in innovation. Understanding this is crucial for assessing how VCs allocate capital and support startups in different technological areas. As the landscape of technological advancements continues to evolve, the impact of VC specialization on startups' success and the broader innovation ecosystem remains a subject of ongoing importance, and further examination of the implications of this trend is at the forefront of my research agenda.

## 1.8 Figures and Tables

FIGURE 1.1: **VC firm specialization at the investment date.** The plot presents the average HHI (Panel A), for VCs' investments since 2000. The specialization index in Panel A is the HHI (as defined in Equation 1.1) of the VC firm computed on all investments up to the day before the focal investment, and it is adjusted for the number of investments made by the VC firm. The first investments of each VC firm are excluded from the plot as their index would mechanically be equal to one. Panel B reports the average share of VC firms in an investment round that has the same sector focus as the focal portfolio company. Sector focus is defined as the industry where the VC firm invested the largest amount of capital to date.

*Panel A: Avg HHI*




*Panel B: Share of VCs in same industry*

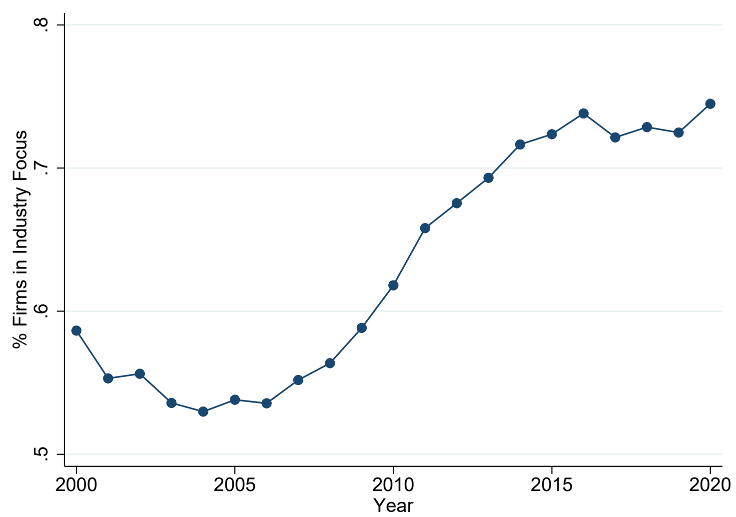


FIGURE 1.2: **Share of first investments by new VC firms, by industry and year.** The figure plots the share of first investments by new VC firms over industry and year buckets. In the years from 2002 to 2005, slightly less than 40% of the first investments by new VC firms were in Software and IT, and approximately 35% in Biotech. That share went up to more than 70% in the decade since 2010 for Software and IT, and down to around 15% for Biotech.

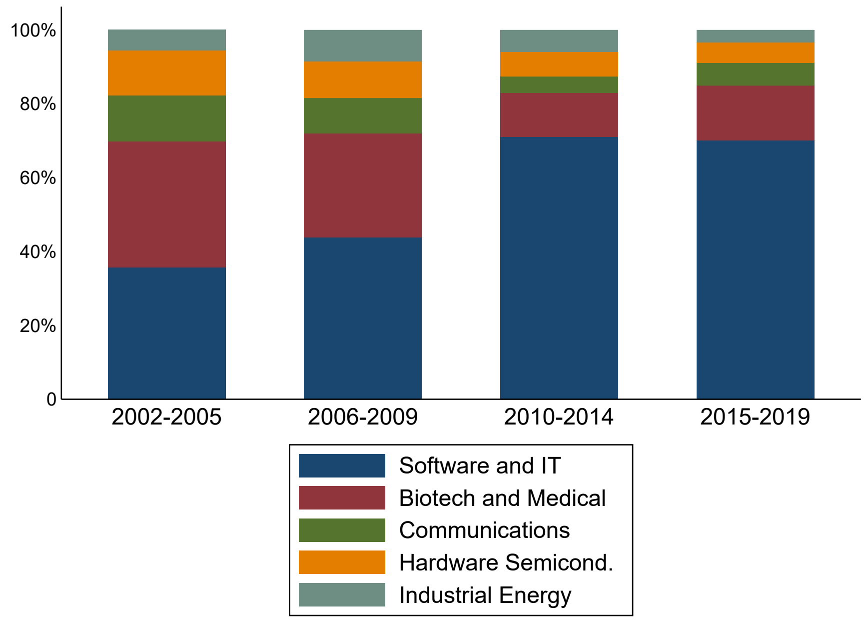


FIGURE 1.3: **Specialization in *deep tech* sectors versus Software and IT over time.** The figure shows the average HHI computed as in Equation 1.1, adjusted by the number of investments by the VC firm, at the investment year, for VCs with sector focus in deep tech (in blue) and in Software and IT (in red). *Deep tech* includes Biotech/Medical, Industrial/Energy, and Hardware/Semiconductors industries. The sector focus is defined as the sector where the VC firm has the highest amount invested.

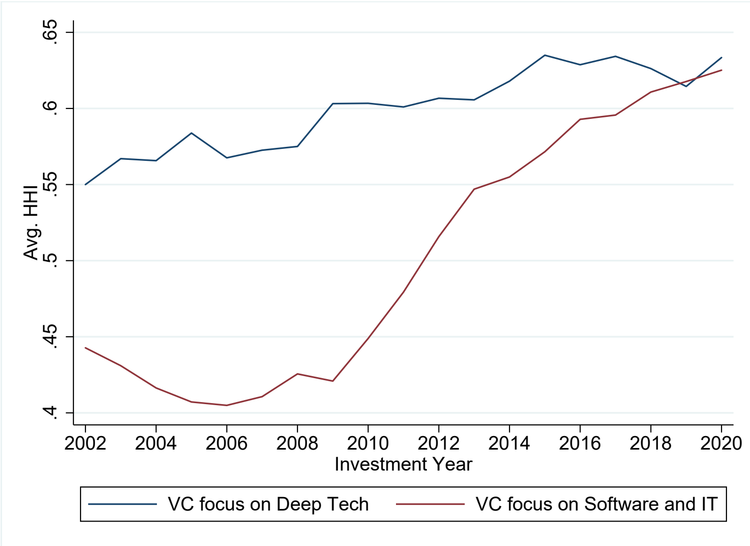
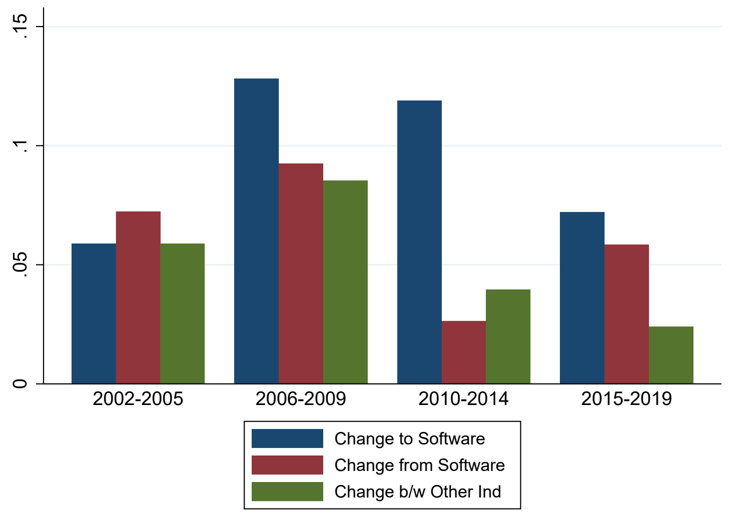


FIGURE 1.4: **Industry change** Using a sample of larger VC firms that raise multiple funds, the plot reports the share of these firms shifting their industry focus towards Software and IT (in blue, Panel A), away from Software and IT (in red, Panel A), and among other industries (in green, Panel A). The shift is identified when a subsequent fund raised by the VC firm has an industry focus (defined by the largest amount invested across different industries) different from the previous funds. Panel B reports the share of new funds raised, that remain in the same focus industry of the VC firm.

*Panel A: Share of VC Firms that change industry focus*




*Panel B: Share of VC Firms that do not change*

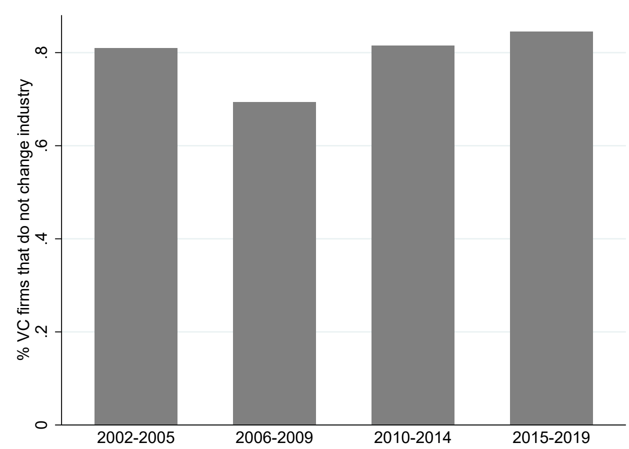


FIGURE 1.5: **Number of VCs and startups in each sector and quarter.** The plot illustrates the number of active VCs and startups, i.e., VCs and startups that close a deal during each quarter. The blue line is the number of different startups that receive financing in the quarter, while the red line is the number of different VCs that make at least one deal. The plot has been created using the lowess method, a statistical technique that provides a smoothed representation of the data, which helps reveal trends in the number of VCs and startups within each industry over time. *Semiconductors and Energy* aggregates the two industries *Hardware and Semiconductors* and *Industrial and Energy*, while *IT Biotech* identifies the companies operating in the Biotech sector and whose business is related to biotech software/bioinformatics.

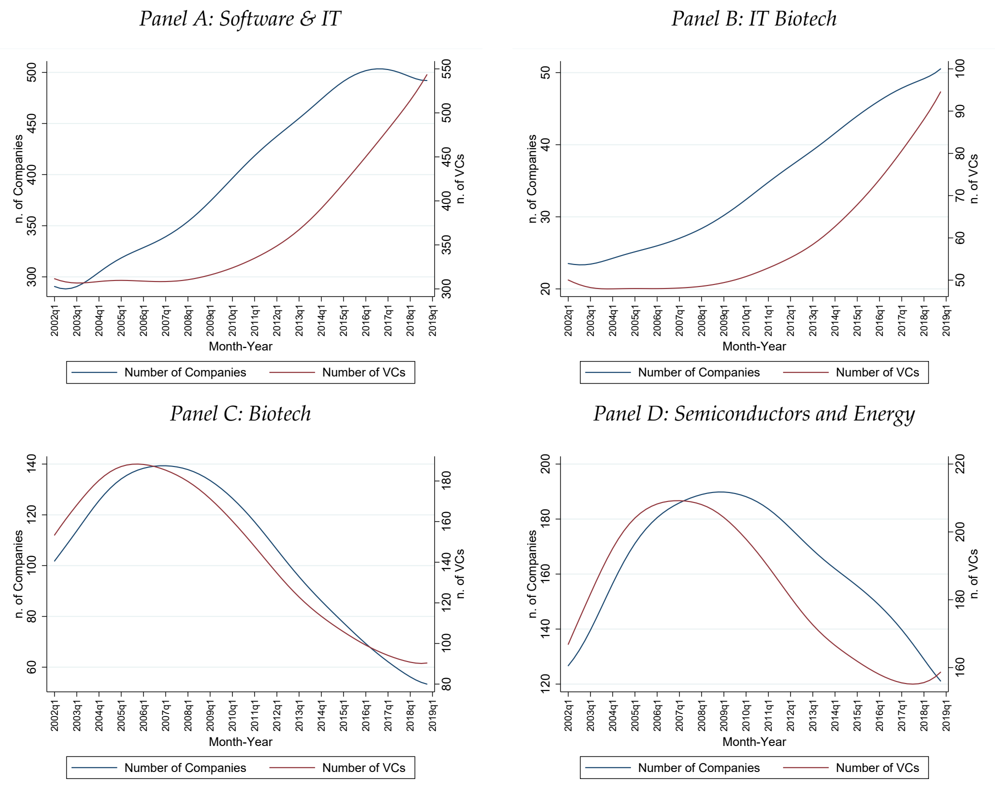


FIGURE 1.6: **Actual vs. predicted probabilities of non-software investments.** The figure plots the actual and predicted probabilities of non-software investments. For the predicted probabilities, the estimation period is 2002-2007. The estimation is performed using a probit model where the dependent variable takes the value of 1 if the investment is in a non-software business. The explanatory variables include company characteristics such as company exit, age, location, and patenting activity (red line), estimation probabilities reported with a green line also include investment and market characteristics such as the first round amount, the quarterly book-to-market of the startup industry, and the lagged number of new software startups. Finally, predicted probabilities plotted with the yellow line also include the HHI of sector specialization of VC firms that have an industry focus on Software and IT.

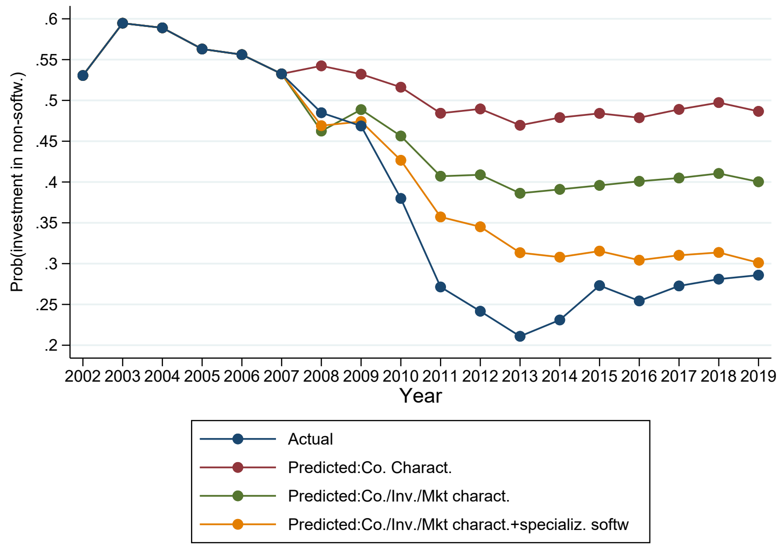


FIGURE 1.7: **VC backing *deep tech* - Evidence from a matched sample.** The plot reports the share of startups in *Treated* vs. *Non Treated* sectors from a matched sample of VC-backed and non-VC-backed innovative young firms in the US Patent and Trademark Office (USPTO) data. Young firms are identified using the data provided by Ewens and Marx, 2024. I then use the technology classes of patents issued by startups to group VC-backed and non-VC-backed startups that innovate in the same sector. Treated startups are portfolio companies whose description has at least one of the keywords “Online”, “E-commerce”, “Hosting”, or “Web”.

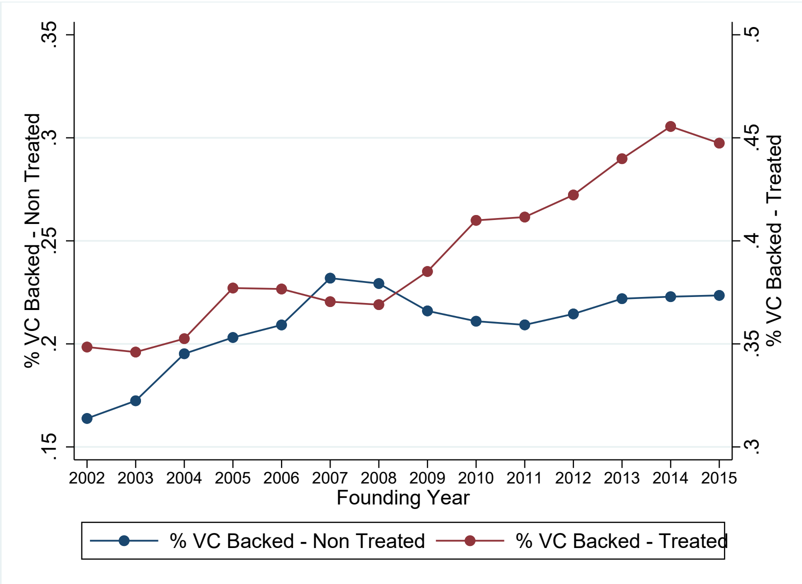
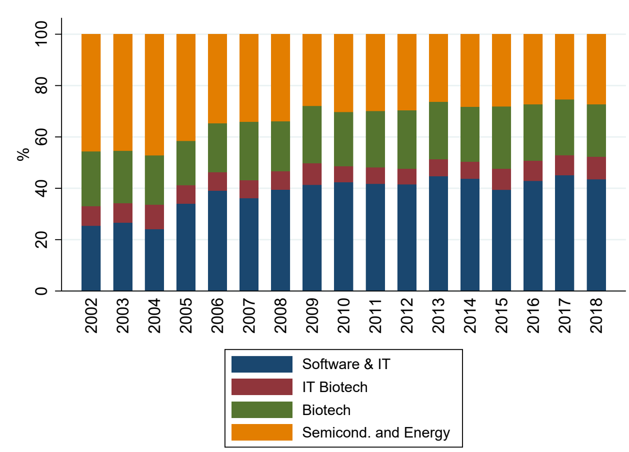


FIGURE 1.8: **The financing of deep tech - Evidence from a matched sample.** The plot reports the distribution of startups across industries, from a matched sample of VC-backed and non-VC-backed innovative young firms in the US Patent and Trademark Office (USPTO) data. Young firms are identified by matching factors like location, inventor count, and years since the first patent (similar to Farre-Mensa, Hedge, and Ljungqvist, 2020, and Gonzalez-Uribe, 2020). I then match the same technology classes of patents issued by startups in the same sector in VenturеXpert, to group VC-backed and non-VC-backed startups that innovate in the same sector. Panel A reports a stack graph where the share is obtained from the number of new startups in each sector, and in Panel B the share is obtained by the number of VCs in the same sectors over the years. The year is the year of the first patent granted to the startup.

*Panel A: Industry distribution of new patenting startups.*




*Panel B: Industry distribution of VC firms.*

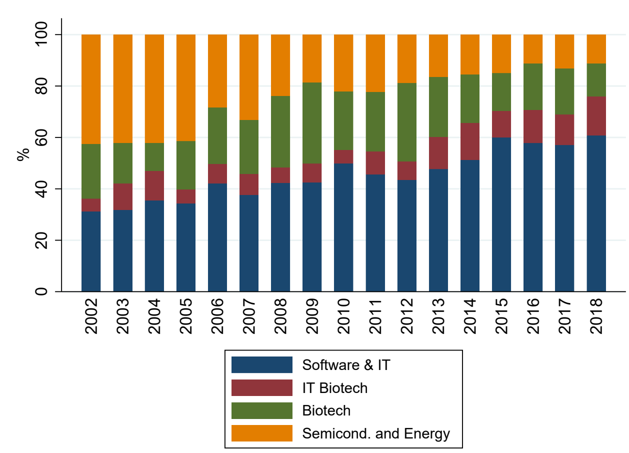


TABLE 1.1: **Descriptive Statistics.** The table reports the descriptive statistics for the main variables used in the analysis. The dataset includes the investment rounds received by a company from a US-based VC firm between January 2002 and December 2019. Panel A reports variables at the VC firm level, Panel B at the Portfolio Company level, and Panel C reports the number of observations at the investment-company level by portfolio company industry, using the main classification used throughout the paper.

| | N Obs<br>(1) | Mean<br>(2) | Std. Dev.<br>(3) | p25<br>(4) | p75<br>(5) |
|---|---|---|---|---|---|
| **Panel A: VC Firm** | | | | | |
| Amount Invested per round ($ mil) | 118,132 | 3.7 | 4.9 | 0.78 | 4.3 |
| N. of Companies | 3,888 | 15.5 | 38.2 | 1 | 13 |
| Firm Vintage Year | 3,888 | 2004 | 11 | 1998 | 2014 |
| 5 yrs HHI Adj. Index | 1,975 | 0.55 | 0.21 | 0.37 | 0.74 |
| **Panel B: Start-ups** | | | | | |
| Round Equity ($ mil) | 60,830 | 7.2 | 10.9 | 1.1 | 8.75 |
| N of Rounds | 60,830 | 3.1 | 2.6 | 1 | 4 |
| N of VCs per round | 46,202 | 2.2 | 1.5 | 1 | 3 |
| Founded Year | 25,409 | 2010 | 6.4 | 2005 | 2016 |
| P(IPO) | 25,409 | 0.06 | 0.24 | 0 | 0 |
| P(M&A) | 25,409 | 0.29 | 0.46 | 0 | 1 |
| P(Fail) | 25,409 | 0.37 | 0.49 | 0 | 1 |
| **Panel C: N. of Observations by Industry** | | | | | |
| | | % | | | |
| Biotech and Medical | 27,519 | 22.85 | | | |
| Hardware and Semiconductors | 11,541 | 9.58 | | | |
| Industrial and Energy | 4,057 | 3.37 | | | |
| Software and Internet | 64,248 | 53.34 | | | |
| Communication and Consumers | 9,188 | 7.63 | | | |
| Other | 3,889 | 3.23 | | | |

TABLE 1.2: **Cost of experimentation between treated and non-treated start-ups.** This table reports averages and t-tests for differences in means for variables describing the characteristics of software vis-à-vis non-software, and bioinformatics vis-à-vis biotech investments after the introduction of cloud computing, and of CRISPR. The column Difference, which reports the t-test, also includes the t-statics for standard errors.

| | Software | | | Biotech | | |
|---|---|---|---|---|---|---|
| Variable | Treated | Non-treated | Diff. | Treated | Non-treated | Diff. |
| Years to exit | 6.31 | 6.67 | -0.364** | 5.04 | 4.61 | 0.43 |
| | | | (-2.69) | | | (1.85) |
| Days to Second Round | 477 | 454 | -13.34 | 453 | 477 | 23.97 |
| | | | (-1.66) | | | (1.14) |
| Initial amount invested | 4.92 | 6.07 | -1.139*** | 5.46 | 7.48 | -2.013*** |
| | | | (-6.59) | | | (-4.09) |

TABLE 1.3: **Investment in Software and IT is a first investment.** The table reports the results of a linear probability model where the dependent variable is an indicator variable that takes the value of 1 if the VC's investment in that company is the first investment ever of the VC, and zero otherwise. Observations are at the first investment by VC in the company level. Column (1) includes as *Treated* companies all companies in the software and IT industry, while columns (2) and (3) identify as *Treated* portfolio companies whose description has at least one of the keywords "Online", "E-commerce", "Hosting", or "Web" in each sector, to provide a sector-segment-level exposure to the treatment, as in Ewens, Nanda, and Rhodes-Kropf, 2018. *Post* is a dummy equal to one if the investment year is after 2006. In all specifications, controls include a natural logarithm of the round's syndicate size (number of investors in the round), dummies for entrepreneurial companies headquarters state, as well as quarterly lagged measure of the median of the yearly book-to-market ratio of all public companies in the same sic2 industry, and a lagged measure of the number of IPOs and M&As. All columns include investment year fixed effects and VC firm fixed effects, and (3) also includes industry fixed effects. Standard errors clustered at the VC investor and investment date level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

| | Probability of First Investment | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Treated X Post | 0.006*** | 0.006*** | 0.007*** |
| | (4.231) | (4.653) | (5.182) |
| Treated | -0.004*** | -0.004*** | -0.003* |
| | (-3.219) | (-3.778) | (-2.030) |
| Observations | 53,319 | 53,321 | 53,320 |
| R-squared | 0.221 | 0.221 | 0.223 |
| Controls | ✓ | ✓ | ✓ |
| Investment Year FE | ✓ | ✓ | ✓ |
| VC Firm FE | ✓ | ✓ | ✓ |
| Industry FE | | | ✓ |

TABLE 1.4: **Increase in specialization post-technological shock.** The table reports the results of an OLS regression where the dependent variable is the natural logarithm of the VC firm's specialization index at investment date, computed as an HHI of capital concentration across industries (as defined in Equation 1.1). Observations are at the company-VC firm investment level. All first and second investments made by a VC are excluded as their HHI would be mechanically equal to 1. In columns (2) and (4) the index is computed using the most granular industry classification available on VentureXpert, which includes more than 500 sectors and considers different end-uses of the startups' technologies. The sample excludes all first investments of a VC firm as their HHI is mechanically equal to 1. Columns (1) and (2) identify as *Treated* portfolio companies whose description has at least one of the keywords "Online", "E-commerce", "Hosting", or "Web" in each sector, to provide a sector-segment-level exposure to the treatment, as in Ewens, Nanda, and Rhodes-Kropf, 2018. Columns (3) and (4) include as *Treated* portfolio companies operating in the Biotech industry and whose business is related to gene editing and/or software/bioinformatics. *Post* is a dummy equals to one if the investment year is after 2006 (AWS introduction) in columns (1) and (2), and after 2013 (CRISPR introduction) in columns (3) and (4). In all specifications, controls include the headquarters location of the startup, as well as a dummy if the startup is located in an entrepreneurial hub, and quarterly lagged measure of the median of the yearly book-to-market ratio of all public companies in the same sic2 industry. All columns include investment year and columns 1 and 2 industry fixed effects. Columns 3 and 4 do not include industry fixed effects because the test is performed on a subsample of biotech companies. Standard errors clustered at the VC investor and investment date level. *** p<0.01, ** p<0.05, * p<0.1

| | VC Firm Specialization | | | |
|---|---|---|---|---|
| | AWS | | CRISPR | |
| | (1) | (2) | (3) | (4) |
| Treated X Post | 0.044*** | 0.034** | 0.095*** | 0.075** |
| | (3.322) | (2.179) | (2.984) | (1.964) |
| Treated | 0.028*** | -0.007 | -0.092*** | -0.045 |
| | (2.745) | (-0.501) | (-2.675) | (-1.258) |
| Observations | 105,465 | 105,465 | 17,440 | 17,440 |
| R-squared | 0.167 | 0.063 | 0.041 | 0.057 |
| Controls | ✓ | ✓ | ✓ | ✓ |
| Investment Year FE | ✓ | ✓ | ✓ | ✓ |
| Industry FE | ✓ | ✓ | | |

TABLE 1.5: **Probability to invest outside industry focus.** The table reports the results of a linear probability model where the dependent variable is an indicator variable that takes the value of 1 if the VC firm in time *t* invests in a company that is outside of the VC's industry focus up to that date. The main independent variable is the VC firm's standardized HHI at the date previous to the focal investment. All first and second investments made by a VC are excluded as their HHI would be mechanically equal to 1. Column (3) includes only the subset of companies whose specialization is in the Biotech and Medical, Industrial and Energy, Hardware and Semiconductors industries. Column (4) only includes VC firms whose industry focus is in the Software, IT, and Communication sectors. On top of control variables at the VC firm level as the log of the VC firm age and the log of VC firm size (i.e., dollar amount invested), in all specifications further controls include a natural logarithm of the round's syndicate size (number of investors in the round), and dummies for entrepreneurial companies headquarters state, a dummy if the company is located in a hub, as well as quarterly lagged measure of the median of the yearly book-to-market ratio of all public companies in the same sic2 industry, and a lagged measure of the number of IPOs and M&As. All columns include investment year fixed effects, and industry fixed effects, and columns (2)-(4) also include VC firm fixed effects. Standard errors clustered at the industry and investment date level. *** p<0.01, ** p<0.05, * p<0.1

| | Probability to Change Industry$_t$ | | | |
|---|---|---|---|---|
| | any industry | | from *deep tech* | from softw.&IT |
| | (1) | (2) | (3) | (4) |
| VC Firm Specialization $_{t-1}$ | -0.120** | -0.037*** | -0.183*** | -0.125** |
| | (-2.775) | (-5.233) | (-7.017) | (-2.672) |
| VC Firm Age | -0.001 | 0.002 | -0.002 | -0.001 |
| | (-1.057) | (0.187) | (-0.676) | (-1.653) |
| VC Firm tot Amt. Inv. | -0.023 | 0.005 | -0.030 | -0.011 |
| | (-1.156) | (0.564) | (-1.898) | (-1.108) |
| Observations | 100,821 | 100,477 | 19,585 | 79,774 |
| Adj.R-squared | 0.512 | 0.591 | 0.337 | 0.161 |
| Controls | ✓ | ✓ | ✓ | ✓ |
| Investment Year FE | ✓ | ✓ | ✓ | ✓ |
| Industry FE | ✓ | ✓ | ✓ | ✓ |
| VC Firm FE | | ✓ | ✓ | ✓ |

TABLE 1.6: **Characteristics of VC firms in biotech and software after AWS.** The table reports the results of an OLS regression where the dependent variables are VC firm characteristics: the log of one plus the VC's age in column (1), the log of the VC size defined as the overall dollar amount invested (column 2), the log of the HHI of the VC's sector specialization in column (3), the market share of the VC firm in the industry-quarter year in column (4), and the log of one plus the syndicate size in column (5). Biotech and Software are indicator variables that take the value of 1 if the portfolio company is in the Biotech or Software sector, respectively. Post is a dummy equal to 1 if the investment happened after 2006. Company Age is the log of 1+ the portfolio company age, and HUB is a dummy that takes value of 1 if the company is located in an entrepreneurial hub. In all specifications, other controls include dummies for entrepreneurial companies headquarters state, the round number of the company, as well as quarterly lagged measure of the median of the yearly book-to-market ratio of all public companies in the same sic2 industry, and a lagged measure of the number of IPOs and M&As. All columns include investment year fixed effects. The unit of observation is at the VC investment-startup level. Standard errors are clustered at the VC investor and investment date level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

| | VC Firm | | | | Syndicate |
|---|---|---|---|---|---|
| | Age | Size ($amt) | Specialization | Market % | Size |
| | (1) | (2) | (3) | (4) | (5) |
| Biotech &Med | -0.032 | -0.321** | 0.105*** | -0.002 | 0.154*** |
| | (-0.519) | (-2.062) | (6.919) | (-0.330) | (5.984) |
| Biotech &Med X Post | 0.088* | 0.371*** | 0.007 | -0.010* | -0.074*** |
| | (1.809) | (3.683) | (0.689) | (-1.646) | (-2.790) |
| Software & IT | -0.026 | -0.086 | 0.044*** | -0.020*** | -0.072*** |
| | (-1.135) | (-1.467) | (10.088) | (-7.401) | (-4.927) |
| Software & IT X Post | -0.021 | 0.041 | 0.013*** | -0.013*** | 0.102*** |
| | (-0.897) | (0.720) | (3.055) | (-3.666) | (6.437) |
| Log of Company Age | 0.116*** | 0.262*** | -0.012*** | 0.000 | 0.054*** |
| | (7.687) | (6.408) | (-3.896) | (0.328) | (5.321) |
| Hub Company | -0.098*** | 0.021 | 0.022*** | 0.001 | 0.071*** |
| | (-4.236) | (0.394) | (4.985) | (0.548) | (7.242) |
| Observations | 100,977 | 102,189 | 102,032 | 102,189 | 102,189 |
| Adj.R-squared | 0.056 | 0.056 | 0.181 | 0.070 | 0.127 |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ |
| Investment Year FE | ✓ | ✓ | ✓ | ✓ | ✓ |

TABLE 1.7: **Characteristics of VC firms in bioinformatics after CRISPR.** The table reports the results of an OLS regression where the dependent variables are VC firm characteristics: the log of one plus the VC's age in column (1), the log of the VC size defined as overall dollar amount invested (column 2), the log of the HHI of sector specialization in column (3), the market share of the VC firm in the industry-quarter year in column (4), the log of 1 + the syndicate size in column (5), and the probability that the investment is a first-ever investment by the VC firm in column (6). Portfolio companies defined as *Treated* are those operating in the Biotech industry whose business is related to gene editing and sequencing, biotech software, or bioinformatics. Post is a dummy equals to one if the investment year is after 2013 (CRISPR introduction). Company Age is the log of 1+ the portfolio company age, and HUB is a dummy that takes the value of 1 if the company is located in an entrepreneurial hub. In all specifications, other controls include dummies for entrepreneurial companies headquarters state, the round number of the company, as well as quarterly lagged measure of the median of the yearly book-to-market ratio of all public companies in the same sic2 industry, and a lagged measure of the number of IPOs and M&As. All columns include investment year fixed effects. The unit of observation is at the VC investment-startup level. Standard errors are clustered at the VC investor and investment date level. *** p<0.01, ** p<0.05, * p<0.1

| | VC Firm | | | | Syndicate | Prob. of |
|---|---|---|---|---|---|---|
| | Age | Size ($amt) | Specialization | Market % | Size | First Inv. |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Treated | -0.005 | -0.014 | -0.106*** | -0.010** | -0.083*** | -0.004* |
| | (-0.124) | (-0.125) | (-5.605) | (-2.275) | (-2.849) | (-1.746) |
| Treated X Post | -0.166*** | -0.257* | 0.050** | -0.014** | 0.103*** | 0.011*** |
| | (-2.675) | (-1.724) | (2.468) | (-2.097) | (2.926) | (2.697) |
| Log of Company Age | 0.002 | -0.049 | 0.001 | -0.001 | 0.081*** | -0.007*** |
| | (0.069) | (-0.697) | (0.124) | (-0.358) | (3.721) | (-3.452) |
| Hub Company | -0.073* | 0.123 | 0.017 | 0.002 | 0.094*** | -0.001 |
| | (-1.790) | (1.265) | (1.135) | (0.788) | (3.401) | (-0.177) |
| Observations | 17,502 | 17,580 | 17,440 | 17,580 | 17,580 | 17,093 |
| Adj.R-squared | 0.075 | 0.103 | 0.046 | 0.034 | 0.132 | 0.212 |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Investment Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| VC Firm FE | | | | | | ✓ |

TABLE 1.8: **Portfolio companies' outcomes.** The table reports the results of a linear probability model where the dependent variables are equal to 1 if the company exited: through IPO in columns (1) and (4), M&A in columns (2) and (5), or failed in columns (3) and (6). To avoid truncation issues due to the post-period, all columns 1-3 consider exits within 10 years since the first investment received by the company. In columns 1 to 3 the main independent variable is the *PostXTreated* interaction consisting of the introduction of AWS services. In columns 4 to 6, the main independent variable is VC firm specialization, computed as an HHI of capital concentration as defined in Equation 1.1, and standardized by subtracting the mean and dividing it by the standard deviation. Observations are at the company-VC firm first investment level. The 10-year threshold is determined to allow equal time to exit in the pre and post-period and avoid truncation issues. Besides the control variables reported, all specifications also include a natural logarithm of the round's syndicate size, of the round number, a lagged measure of the number of IPOs and M&As, and the lag amount of capital fundraised. Controls at the investor level also include the market share of the VC firm in the quarter and a dummy that equals 1 if the firm is a corporate VC. The choice of control variables follows Nahata, 2008. Columns 1-3 include investment year and industry fixed effects, and columns 4-6 include investment year times industry fixed effects. Standard errors clustered at the VC investor and investment date level. *** p<0.01, ** p<0.05, * p<0.1

| | AWS | | | VC Specialization | | |
|---|---|---|---|---|---|---|
| | IPO 10yrs (1) | M&A 10yrs (2) | Failed (3) | IPO 10yrs (4) | M&A 10yrs (5) | Failed (6) |
| Post X Treated | -0.009 | -0.033** | 0.025** | | | |
| | (-0.950) | (-1.992) | (2.236) | | | |
| Treated | 0.019** | 0.015 | -0.050*** | | | |
| | (2.380) | (0.930) | (-4.799) | | | |
| VC Specialization | | | | 0.005* | 0.005 | -0.010*** |
| | | | | (1.738) | (1.036) | (-2.724) |
| Observations | 29,836 | 29,836 | 29,836 | 28,484 | 28,484 | 28,484 |
| Adj. R-squared | 0.097 | 0.038 | 0.242 | 0.104 | 0.039 | 0.247 |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Investment Year FE | ✓ | ✓ | ✓ | | | |
| Industry FE | ✓ | ✓ | ✓ | | | |
| Industry X Year FE | | | | ✓ | ✓ | ✓ |

## References

Ben-David, Itzhak et al. (Aug. 2022). "Competition for Attention in the ETF Space". In: *The Review of Financial Studies* 36.3, pp. 987–1042.

Bernstein, Shai, Xavier Giroud, and Richard R. Townsend (2016). "The Impact of Venture Capital Monitoring". In: *The Journal of Finance* 71.4, pp. 1591–1622.

Blickle, Kristian, Cecilia Parlatore, and Anthony Saunders (2021). "Specialization in Banking". In: *Federal Reserve Bank of New York Staff Reports, no. 967*.

Bonelli, Maxime (2023). "Data-driven Investors". In: *Working Paper*.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer (Nov. 2015). "Competition for Attention". In: *The Review of Economic Studies* 83.2, pp. 481–513.

Brinster, Leonhard and Tereza Tykvova (2021). "Connected VCs and strategic alliances: Evidence from biotech companies". In: *Journal of Corporate Finance* 66.

Brown, Gregory W., Celine Yue Fei, and David T. Robinson (2023). "Portfolio Management in Private Equity". In: *Working Paper*.

De Jonghe, Olivier et al. (Jan. 2019). "Some Borrowers Are More Equal than Others: Bank Funding Shocks and Credit Reallocation*". In: *Review of Finance* 24.1.

Ewens, Michael and Matt Marx (2024). "Founding Patents: Young Firm Innovation". In: *Working Paper*.

Ewens, Michael, Ramana Nanda, and Matthew Rhodes-Kropf (2018). "Cost of experimentation and the evolution of venture capital". In: *Journal of Financial Economics* 128.3, pp. 422–442.

Ewens, Michael, Ramana Nanda, and Christopher Stanton (2023). "Founder-Ceo Compensation and Selection into Venture Capital-Backed Entrepreneurship". In: *Working Paper*.

Farre-Mensa, Joan, Deepak Hedge, and Alexander Ljungqvist (2020). "What Is a Patent Worth? Evidence from the U.S. Patent "Lottery"". In: *The Journal of Finance* 75.2, pp. 639–682.

Fernandez, Jose-Maria, Roger M Stein, and Andre W Lo (2012). "Commercializing biomedical research through securitization techniques". In: *Nat Biotechnol.*

Fulghieri, Paolo and Merih Sevilir (Mar. 2009). "Size and Focus of a Venture Capitalist's Portfolio". In: *The Review of Financial Studies* 22.11, pp. 4643–4680.

Gompers, Paul, Will Gornall, et al. (2020). "How do venture capitalists make decisions?" In: *Journal of Financial Economics* 135.1, pp. 169–190.

Gompers, Paul, Anna Kovner, and Josh Lerner (2009). "Specialization and Success: Evidence from Venture Capital". In: *Journal of Economics & Management Strategy* 18.3, pp. 817–844.

Gonzalez-Uribe, Juanita (2020). "Exchanges of innovation resources inside venture capital portfolios". In: *Journal of Financial Economics* 135.1, pp. 144–168.

Hall, Bronwyn H., Adam B. Jaffe, and Manuel Trajtenberg (Oct. 2001). "The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools". In: *NBER Working Paper* 8498.

Hoberg, Gerard and Nagpurnanand R. Prabhala (2009). "Disappearing Dividends, Catering, and Risk". In: *The Review of Financial Studies* 22.1, pp. 79–116.

Hochberg, Yael V., Michael J. Mazzeo, and Ryan C. McDevitt (2015). "Specialization and Competition in the Venture Capital Industry". In: *Review of Industrial Organization*.

Hodgson, Leah (2023). "Battle of the funds: Do VC specialists outperform generalists?" In: *Pitchbook News and Analysis*.

Inderst, Roman and Holger M Müller (2004). "The effect of capital market characteristics on the value of start-up firms". In: *Journal of Financial Economics* 72.

Jack, Andrew (2023). "Non-profit and industry investors propose paediatric cancer fund". In: *Financial Times*.

Jones, Benjamin F. (2009). "The Burden of Knowledge and the "Death of the Renaissance Man": Is Innovation Getting Harder?" In: *The Review of Economic Studies* 76.1, pp. 283–317.

Lerner, Josh and Ramana Nanda (2020). "Venture Capital's Role in Financing Innovation: What We Know and How Much We Still Need to Learn". In: *Journal of Economic Perspectives* 34.3, pp. 237–261.

Marx, Matt and Aaton Fuegi (2020). "Reliance on science: Worldwide front-page patent citations to scientific articles". In: *Strategic Management Journal* 41, pp. 1572–1594.

Michelacci, Claudio and Javier Suarez (2004). "Business Creation and the Stock Market". In: *The Review of Economic Studies* 71.2, pp. 459–481.

Mitchell, Peter (2009). "Venture capital shifts strategies, startups suffer". In: *Nature Biotechnology* 27.2, pp. 103–104.

Nahata, Rajarishi (2008). "Venture capital reputation and investment performance". In: *Journal of Financial Economics* 90.2, pp. 127–151.

Nakamae, Kazuki and Hidemasa Bono (2022). "Genome editing and bioinformatics". In: *Gene and Genome Editing*.

Nanda, Ramana and Matthew Rhodes-Kropf (2017). "Innovation Policies". In: *Working Paper*.

Sorensen, Morten (2008). "Learning By Investing: Evidence from Venture Capital". In: *AFA 2008 New Orleans Meetings Paper*.

Spaenjers, Christophe and Eva Steiner (2023). "Specialization and Performance in Private Equity: Evidence from the Hotel Industry". In: *Working Paper*.

# 2 From in-person to online: the new shape of the VC industry

*with Liudmila Alekseeva, Caroline Genc, and Hedieh Rashidi Ranjbar*

## 2.1 Introduction

> *"I think the biggest challenge is the inability to go visit somebody, to walk around their office, to get a feel for their culture"*
>
> *Roelof Botha, VC at Sequoia Capital*

In-person interactions have been perceived as crucial in the venture capital (VC) industry both for the selection process and post-investment activities (Bernstein, Giroud, and Townsend, 2016). As VCs invest in early-stage companies with little available information, they have to rely on soft information about their investment targets. This type of information cannot be easily summarized by a numeric score and reliably transferred through distance. Therefore, to accumulate and exchange soft information, VCs spend much of their time networking (Gompers, Gornall, S. K. Kaplan, et al., 2020) and locate in entrepreneurial clusters facilitating frequent face-to-face interactions (Sorenson and Stuart, 2001). Nevertheless, the literature has not yet explored if in-person interactions are an essential feature of the VC investment model or simply a result of historical norms.

One way to answer the question about the importance of in-person interactions for the VC industry is to study the consequences of restricting such interactions. In this paper, we exploit the sudden interruption of in-person communication due to the recent pandemic to explore changes in VC investments when all face-to-face communication is replaced by online meetings. Roelof Botha, a VC at Sequoia Capital, one of the largest VC firms in the United States, reported: *"I think the biggest challenge is the inability to go visit* *somebody, to walk around their office, to get a feel for their culture."*[1] Even though online interactions might be a good substitute for in-person ones, they seem imperfect.

To assess the necessity of meeting in person for VCs, we first test if the geography of their investments changes following the pandemic-driven restrictions. We then analyze shifts in the VC investment behavior, including investment selection and syndication processes. Using comprehensive Pitchbook data on VC financing, we build our analysis on two approaches. First, an event study uncovers changes in VC investments relative to the long-term trends of this industry. Second, we extend our findings by documenting causal evidence in a difference-in-differences setting.

For the difference-in-differences analyses, we exploit the heterogeneity in VCs' potential capacities to respond to a shock to in-person communication by switching to online interactions. More specifically, we use a continuous measure of VCs exposure to remote-work friendly industries (Dingel and Neiman, 2020) before Covid-19 as treatment intensity.[2]

We argue that VCs with a history of investments in industries with high remote-work feasibility are better equipped to make online investments. Their past focus on such industries might encourage them to continue investing in remote-work-friendly sectors. Moreover, their potential experience with online interactions gives them an advantage in navigating the digital investment landscape.[3] Therefore, they could better adapt their investment behavior when Covid-19 forced restrictions on in-person interactions. Indeed, given the nature of businesses in remote-work-friendly industries, which require less interpersonal communications and can be effectively performed from home, VCs with a higher exposure could potentially make online investments even before the pandemic if in-person interactions were not a VC

[1]From *McKinsey on startups* podcast. See https://www.mckinsey.com/industries/technology-media-and-telecommunications/our-insights/global-vc-view-funding-startups-in-the-next-normal.

[2]We rely on a difference-in-differences setting with continuous treatment where entities receive different doses or intensities of treatment (see Callaway, Goodman-Bacon, and Sant'Anna, 2024 for a theoretical approach and J. Chen and Ewens, 2021 for an empirical application example).

[3]Investing in a software and online-related business offers the benefit of more easily monitoring companies compared to sectors such as biotech or energy that have to rely more on on-site visits. This view is also supported by several informal interviews we conducted with VC practitioners who confirm that the former might be more suitable for online fundraising. While software companies can easily show the demo of their product online, deep and hard tech companies would still require to be visited in person.

industry norm and considered essential to collecting soft information.[4]

Hence, the variation in VCs' pre-pandemic exposure to remote-work industries allows us to test how a change in soft information collection from in-person to online impacted these financial intermediaries' investments. We expect the pre-pandemic familiarity of VCs with remote-work-friendly industries to give them an advantage over VCs with less exposure in their response to the changes in the VC investment environment. Our estimation strategy enables us to include strict fixed effects, such as *VC State* × *Year* and *Company State* × *Industry* × *Year*, to compare investments made in the same state, industry, and year by VCs with different exposure to the remote-work industries, while controlling for the market conditions to which these VCs are exposed. Thus, introducing these detailed fixed effects enables us to rule out several alternative explanations that could drive the observed changes (such as the inflow of VC capital, the local competition in the VC industry, changes in the supply of startups in different industries and states, etc.).

Historically, distance has posed a significant barrier to soft information collection, as it leads to higher costs of communication with remote parties (Petersen and Rajan, 2002; Agarwal and Hauswald, 2010). Since pandemic-related restrictions forced investors to interact online with all firms, the gap in the quality of soft information and the cost of its collection between proximate and distant companies was reduced. Thus, as soft information collection was no longer facilitated by proximity in this new environment, we expect VCs to break their traditional investment model and invest in more distant startups. Such a change would be particularly strong for those highly exposed to remote-work industries. These VCs are better equipped to quickly transition to online investments and explore opportunities beyond their usual geographic reach due to the expanded range of options accessible online.

In line with our predictions, distance post-Covid exhibits a rise of 35% between a VC firm and its portfolio company in a cross-section of all first-round VC investments (this increase of distance relative to the averages we observe in the data is nearly equivalent to a New York-based VC with all its investments in Chicago before Covid making all its investments in Minneapolis after Covid). In specifications with VC firm fixed effects, we observe a distance increase of 20%. Since distance between financial intermediaries and small businesses has been increasing for decades (Petersen and Rajan, 2002), we also check for and document the existence of a long-term increasing trend in

[4]Tests of parallel trend assumption show that before the pandemic VCs that had more exposure to remote-work friendly industries did not have a significantly different investment behavior from VCs with less exposure to such industries.

distance between VCs and their portfolio companies. Therefore, our results show that the pandemic significantly accelerated an already existing trend, not yet shown by prior literature.[5] We then find that this increase in distance translates into VCs being 13% more likely to invest outside their state borders after Covid. These changes also reflect some redistribution of the number of VC investments from large entrepreneurial hubs toward non-hub areas.

Finally, we observe the persistence of the distance increase even after the pandemic restrictions are lifted. This finding is consistent with the ongoing presence of remote fundraising highlighted by entrepreneurs and VCs in our informal interviews.

We provide evidence of a causal effect of the switch to online communications during the pandemic on the changing geography of VC investments using the difference-in-differences approach described earlier. We find that the distance increase between VC investors and their portfolio companies is primarily driven by VCs more exposed to industries with a high feasibility of work from home (WFH) before the pandemic. VC investors with 10% higher exposure to remote-work industries are located up to 15% farther away from their portfolio companies and invest less frequently in their own state after the start of the pandemic.

These results hold even when accounting for the most restrictive fixed effects that control for time-varying changes in the VC's state of location, as well as the startup's state and industry.

More specifically, we try to ensure that our results are not driven by overall changes in the economic conditions, movements of entrepreneurs to and from different states, increase in attractiveness of specific industries, increase in demand for VC financing in specific states and inflows of capital to VCs' states post Covid-19. Our difference-in-differences empirical setting, restrictive fixed effects, and control variables that we use help us to achieve this goal. To strengthen that changes in soft information collection is the channel behind our findings, we run several robustness tests. In particular, we show that our results remain strong when excluding companies that were likely to benefit from the pandemic, or retaining only companies that were established before 2019. Our results are also robust to focusing on lead VCs' deals and using different ways to define treatment via continuous and dummy variables.

[5] This means that our event study results are robust to including a time trend. In the difference-in-differences regression model, the time trend is absorbed by fixed effects.

To corroborate the mechanism underlying our findings, we test the heterogeneity in distance increase depending on the Covid-related restrictions and the severity of Covid shock in VCs' states, similar to Han et al., 2022 for the analysis in the Chinese market. If the growth of distance between VC investors and portfolio companies is primarily driven by the restriction of in-person interactions, we can expect that VCs located in states that experienced a larger shock from the pandemic would be more likely to switch to online communications and engage in more remote investments. Our results support this hypothesis as well.

These distance-related findings raise further questions about the necessity of in-person interactions to collect soft information. Do these results suggest that VCs do not need such interactions to gather the information they used to have? Or do VCs find a way to balance the limited access to this information? To answer these questions and to understand how VCs respond to the lack of in-person due diligence, we examine changes in their investment characteristics. If in-person interactions are not essential to acquire soft information or if online communication provides a perfect substitute for in-person meetings to collect such information, we should not observe significant differences before and after Covid. On the contrary, if online meetings cannot fully replace in-person ones, there should be changes in VCs' investment types and ways of structuring deals.

We find changes in both VC investments and syndication processes. Post-Covid, VCs select investments that are more familiar to them and rely more on the industry expertise of their syndicate. However, VCs with a higher exposure to remote-work industries do so to a lesser extent. In line with our baseline assumptions, reduced necessity to compensate for the absence of in-person meetings or better ability to explore novel opportunities online for such investors might explain this finding. Regarding syndicate formation, although historically VCs co-invest more and build larger syndicates when they invest in distant startups (Sorenson and Stuart, 2001), we find that this is no longer the case, perhaps due to an increased difficulty of forming syndicates in a post-pandemic world. We also observe that, irrespective of their exposure to remote-work industries, VCs are more inclined to partner with known syndicate members. This suggests that in a new environment, VCs prefer reaching a trusted network. Also, consistent with our distance-related findings, we show that the average distance across syndicate members increases post-Covid, with VCs with higher exposure to remote-work sectors co-investing with more distant partners. Overall, these findings suggest that online interactions do not entirely substitute for in-person ones and cannot overcome frictions that might be associated with distance for most VC investors.

In an additional analysis, we provide early insights on the performance of VC investments that were deal-sourced online rather than in-person. Due to the limited time since the start of the pandemic, we primarily focus on the probability of raising a second financing round as a main intermediate performance indicator. We find that companies receiving their initial VC funding post-Covid are more likely to secure a second round, regardless of VCs' exposure to remote-work industries, suggesting that online-sourced deals do not perform worse than pre-pandemic ones. Nevertheless, future research covering a more extended post-Covid period will be able to shed light on how critical in-person interactions are for VCs' long-term performance.

Our paper contributes to different strands of literature. As soft information is a key driver of VCs' investment decisions, our study is strongly related to this literature (e.g., Petersen and Rajan, 2002; Stein, 2002; Berger et al., 2005; Liberti and Petersen, 2018). We contribute to this stream by providing evidence that online interactions cannot perfectly substitute for in-person meetings when VCs select new companies for investments.

With these results, we complement the prior findings by Bernstein, Giroud, and Townsend, 2016 on the importance of VCs' on-site monitoring of portfolio companies. We show that, indeed, VCs are not indifferent to the restrictions, and some of them compensate for the lack of face-to-face interactions by relying more on their expertise and networks. Highlighting the importance of networks in such conditions, we supplement prior studies on the role of social networks for information exchange in the VC industry (Bygrave, 1987; Sorenson and Stuart, 2001; Casamatta and Haritchabalet, 2007; Hochberg, Ljungqvist, and Lu, 2007; Hochberg, Ljungqvist, and Lu, 2010; Hochberg, Lindsey, and Westerfield, 2015; Zhang, Gupta, and Hallen, 2017).

Our paper then adds to the literature on the geography of the VC industry (e.g., Sorenson and Stuart, 2001; Bengtsson and Ravid, 2009; Cumming and Dai, 2010; H. Chen et al., 2010). It reveals that while communication technologies long ago created the opportunity to change the traditional VC investment model based on geographical clustering and in-person communication, the restriction on in-person activities during the Covid-19 pandemic accelerated this change.

By showing that some VCs reallocate investments outside of hubs, our results suggest a potential departure from the VC investment model characterized by strong geographical clustering (H. Chen et al., 2010; Cumming and Dai, 2010). Moreover, the observed increase in distance among syndicate partners aligns with the spatial patterns of VC investments described in Sorenson and Stuart, 2001.

Finally, our study contributes to a growing literature on the impact of Covid-19 on entrepreneurship and the VC industry (e.g., Howell et al., 2020; Buffington et al., 2020; Fairlie, 2020; Gompers, Gornall, S. N. Kaplan, et al., 2021; Fazio et al., 2021; Bellucci et al., 2023; Han et al., 2022). We complement the research of Gompers, Gornall, S. N. Kaplan, et al., 2021 and Howell et al., 2020 by uncovering a major change in VCs' behavior: their increased propensity to invest farther away, alongside changes in the investment selection criteria and in syndication processes. While Gompers, Gornall, S. N. Kaplan, et al., 2021 provide survey-based evidence that Covid-19 made VC firms more willing to invest outside their home region, we use actual investment data to support that, post Covid-19, VCs invested in startups that were farther away and quantify the extent of this effect.

In addition, studying the characteristics of companies selected by VCs post Covid-19 and the structure of VCs' syndicates uncovers a key contribution of our research: online interactions do not entirely substitute for in-person ones. While the widespread usage of online communication softwares motivated VCs to invest in startups that were farther away from them, we find that these tools were not perfect substitutes for in-person interactions in terms of acquiring information about the targeted companies.

Moreover, Bellucci et al., 2023 show that VCs' portfolios contain now more companies that could benefit from the pandemic and Srivastava and Gopalakrishnan, 2022 show that companies more amenable to work from home can attract larger amounts of financing. Motivated by their findings, we design the empirical strategy to alleviate these alternative explanations and show that our results are not likely to be driven by such changes.[6]

Our paper is the first to document this increased distance in the US-based VC investments while also accounting for a decade-long trend and exploiting the heterogeneity of VCs in a difference-in-differences setting. In a limited five-year sample, Han et al., 2022 find similar results on investment distance.

[6]More specifically, given that attractiveness of specific industries post Covid-19 could be a reason for VCs' investments outside of their home region, we included *Company State* $\times$ *Year* and *Company State* $\times$ *Industry* $\times$ *Year* fixed effects in our regressions. These fixed effects absorb the effects of changes in the attractiveness of industries over time, or the effects of changes in demand for VC investments in industries over time.

Our study goes further, untangling the mechanism behind this increase in distance and showing that VCs compensate for the lack of soft information with their expertise and by making investments similar to their previous ones. Additionally, we explore changes in VC syndicates, showing that VCs now rely more on their established networks.

Our findings have a range of important implications. First, they highlight the diffusion of entrepreneurial activity and innovation spillovers outside traditional hubs. As VCs expand the geography of their investments, a possible decline in the importance of traditional clusters of entrepreneurship raises new questions for future research.

While the positive and significant time trend in our regressions highlights that reallocation of investments from the typical hubs has been underway for a few years, the pandemic seems to have accelerated this tendency for VCs that are more exposed to remote-work sectors. Second, we document that VCs leverage their existing knowledge by investing in industries and businesses that share more similarities with past VC investments. Thus, VCs look more cautious when choosing companies for online investment. This might have implications for the types of innovative companies that can obtain VC financing online in the future. Finally, we observe that VCs are relying more on their networks than before. They co-invest in smaller and more geographically dispersed syndicates, but with investors they already know from before and with industry experts. These results have implications for the evolution of VC networks because if VCs find it more crucial or easier to engage with their peers, the role of networks is likely to increase.

Overall, our results imply that even with a shock that forced the adoption of online communications, VCs took careful steps towards changing their behavior, suggesting that the complete replacement of in-person with online interactions is not around the corner.

The remainder of the paper is organized as follows: we describe the data in Section 2.2, while Section 2.3 presents our estimation strategy. Section 2.4 examines the new geographical scope of the VC industry and Section 2.5 details changes in investment characteristics and syndication process. Section 2.6 concludes.

## 2.2 Data

To obtain information on VC investments, we use Pitchbook, given that it is considered one of the most comprehensive data sources about VC investment rounds.[7] It provides detailed information on deal characteristics, investors, and portfolio companies. For our analysis, we concentrate on investment rounds conducted by U.S.-based VC firms. To restrict our focus to VC deals, we first keep in our dataset investors whose *Primary Investor Type* is either "Venture Capital", "Corporate Venture Capital" or "Accelerator/Incubator"[8]. We then exclude deals without VC round information and those corresponding to Angel rounds. Lastly, we limit our observations to those with a "Venture Capital" deal class. Since we are interested in the VCs' selection of new investments when little hard information is available about them, we further restrict our dataset to the first rounds of financing received by U.S.-based portfolio companies and classified as "seed" or "early-stage".

Our dataset covers investments made between March 2013 and July 2022. To make our analysis more intuitive, we redefine years based on the Covid-19 onset in the U.S.: each year starts in March and ends in February.[9] Our final sample contains 46,652 observations at the VC investor-startup level and includes 19,805 unique entrepreneurial companies financed by 4,357 unique investors. When considering only lead VC investors for each deal, the sample contains 19,805 observations with 3,263 unique lead investors.

Table 2.1 presents descriptive statistics for the key variables used in the analysis (defined in Table 2.11) at the investor-startup level. It shows that the average deal concerns an investor 1,318 km away from the portfolio company and located in the same state as the target company with the probability of 51%. The average deal in our sample involves almost four VCs, and 64% of the deals represent a seed stage. The average company in a VC's portfolio is 3 years old at the time of receiving the analyzed investment, and it is 49% likely to be located in an entrepreneurship hub.[10]

For the difference-in-differences analysis, we define the "work-from-home" exposure at each VC level using the VC's portfolio composition before the

[7]A previous version of this paper that focused only on the event-study method was written using Refinitiv data for the main analysis and Pitchbook for some limited analyses. To ensure the consistency of the data across the overall analysis, we use Pitchbook data on VC investments throughout the paper in this version. However, our results showed qualitatively the same results with both Refinitiv and Pitchbook datasets.

[8]Unreported results confirm that our findings remain robust after excluding the "Corporate Venture Capital" or "Accelerator/Incubator" categories from the analysis.

[9]March 2020 is considered as the beginning of the Covid-19 onset in the U.S based on the timing of Covid-related restrictions (see Table 2.12 for the summary of the restrictions intensity in states with the largest VC investor presence).

[10]Hubs are the ten largest cities by the number of startups in our sample before Covid, including San Francisco, New York, Boston, Seattle, Austin and others.

pandemic.[11] The estimation of WFH exposure is based on an industry-level measure proposed by Dingel and Neiman, 2020. This measure is constructed using surveys from US workers' occupations to identify whether their jobs can be entirely done from home. According to their score that goes from 0 (minimum WFH feasibility) to 1 (maximum WFH feasibility), sectors that include Computer and Mathematical Occupations, Education, or Legal Occupations, have a score close to 1. On the contrary, sectors including a large proportion of Construction and Extraction Occupations, Food Preparation and Serving Related Occupations, Building and Grounds Cleaning and Maintenance Occupation, have a score close to 0. To estimate the WFH feasibility for the startups in our data, we manually map 2-digit NAICS industries from the data of Dingel and Neiman, 2020 to industry classifications available in Pitchbook (Table 2.13 provides examples of startup industries and their estimated WFH score). We then calculate the weighted average of WFH feasibility of startups a VC invested in before the pandemic using deal sizes as weights. Table 2.1 shows that the mean *WFH Exposure* score for a VC is around 0.50 in our sample. As an illustrative example, among VCs with more than 30 deals in our sample, a VC with an above average WFH-score is *Clocktower Technology Ventures*, a firm investing primarily in fintech and having a WFH exposure score of 0.65. On the opposite side, VC firms with a lower score include *Clean Energy Ventures* (score of 0.31), which is a VC specialized in cleantech, and *Lux Capital* (0.44), that invests in science-based *Deep Tech* startups in biotech and healthcare.

We supplement our data with VC fundraising information from Refinitiv for U.S.-based VC funds to estimate a control for the VC capital available for investment at the state level. As the long-term relationship between fundraising and distance is positive and significant (see Table 2.14), we include this variable in all our analyses that do not include fixed effects for the state-level time trends to control for changes in the VC fundraising environment.

## 2.3 Estimation strategy

To systematically analyze changes in the VC industry following restrictions on in-person meetings, we use two empirical strategies: event study and difference-in-differences methodologies. Event study regressions reveal the overall change in VC investment patterns relative to the long-term trends

[11] We use all deals VC investors performed between March, 2013 (the start of our data) and February, 2020 to estimate VCs' *WFH Exposure* measure.

observed in the pre-pandemic period. The difference-in-differences strategy enables us to identify the causal effect of the pandemic and establish the mechanism behind the observed changes.

### 2.3.1 Empirical setting

In financial relationships involving small and opaque businesses (small business lending, venture capital, and real estate), soft information plays a key role, and in-person interactions are perceived as crucial for its collection. Since it is more difficult and costly to communicate with distant partners, distance is perceived as a friction to soft information acquisition (Petersen and Rajan, 2002; Agarwal and Hauswald, 2010; Giroud, 2013). This explains why geographical clustering is frequent in industries that depend on soft information. However, with the adoption of new communication technologies, the availability of timely hard information increased, and the use of soft information in lending relationships was reduced. As a result, the distance between small firms and their lenders has been increasing for decades. Although the VC industry wasn't exempt from this technology adoption, it is one of the industries where geographical clustering still remains strong: face-to-face and informal meetings have been a norm in the VC industry. As Guy Turner, a VC investor at *Hyde Park Venture Partners*, wrote about it in 2018: *"We have only ever seen one term sheet (of many) without a visit. And why would we? Imagine someone investing millions of dollars sight unseen"*.[12]

The Covid-19 pandemic created a strong, unexpected stress on this norm: it interrupted all in-person meetings and forced widespread adoption of teleworking. In March 2020, U.S. state governments imposed unprecedented restrictions on people's movement and face-to-face interactions. Many states started by closing schools and canceling large public gatherings. Then, closures extended to workplaces, and all non-essential workers were required to stay at home. By the end of March, all U.S. states had introduced strict distancing measures, and everyone who could, started working from home. Many, if not all, business meetings were replaced by online meetings. The widespread switch to video communication services such as Zoom, Microsoft Teams, Skype, or similar software can be observed in the surging stock prices

[12]From "Flying for money: How to raise Series A and B outside Silicon Valley" blog-post. See https://vcwithme.co/2018/02/12/flying-for-money-how-to-raise-series-a-and-b-outside-silicon-valley/

of their providers, reflecting how crucial web conferencing has become. Therefore, all firms, whether very close to each other or not, were forced to interact in the same way: online. While VC investors highly value face-to-face meetings due to the lack of tangible information about the quality of young startups, startup demos, networking events, and dinners with founders were no longer possible. VCs had to adopt videoconferencing as the primary tool to keep learning about investment opportunities, meet startup founders, and monitor portfolio companies.

Hence, the advantageous edge of proximity for information collection diminished after the pandemic outbreak. This reduced the gap in the quality of soft information and the cost of its collection between proximate and distant startups. The Chief Executive Officer of Silicon Valley Bank described the new communication ways explored by VCs in an earnings call in October 2020: *"Everyone was doing it [Zoom calls] and they were just talking about how efficient it was and how this maybe a new normal and allow them to look at investments more broadly in different markets"*.[13] Thus, we expect that, in these new conditions, VCs break the traditional norm and expand their horizons, seeking promising investments beyond the usual borders.

To further understand how such restrictions affected VCs' selection process and investment strategies, we explore changes in their investment characteristics. We first investigate whether VCs adjust their selection criteria towards company characteristics that could proxy for the potential availability of hard information and diminish the need to obtain extensive soft information and conduct in-person visits. We then analyze if the decrease in in-person interactions makes it harder for VCs to reach out to their networks or if the need to collect information about investment opportunities increases the inter-VCs relationships.

On the one hand, if online and in-person interactions prove to be perfect substitutes, we should not see any significant change in VCs' investment selection behavior. On the other hand, we can expect VCs to adjust their investment selection criteria and syndicate formation post-pandemic to compensate for the difficulty of obtaining soft information, if online and in-person interactions are not perfect substitutes.

[13] From: SVB financial group CEO Gregory Becker on Q3 2020 results - earning call transcript. Dow Jones Institutional News. See https://www.proquest.com/wire-feeds/svb-financial-group-ceo-gregory-becker-on-q3-2020/docview/2453841304/se-2

### 2.3.2 Event study analysis

We first focus on changes in the VC industry by comparing VCs' investment practices after the Covid-19 onset (between March 2020 and July 2022) with their pre-Covid investments (from March 2013 to February 2020). We estimate the following specification at the VC investor-company-year level:

$$Y_{i,j,t} = \beta_1 Post\ Covid_t + \beta_2 Time\ Trend + X'\theta + \alpha_i + \gamma_s + \eta_{b\times l} + \omega_m + \epsilon_{i,j,t} \tag{2.1}$$

The dependent variable $Y_{i,j,t}$ refers to the characteristics of an investment made by investor $i$ in company $j$ at time $t$. When analyzing the distance between an investor $i$ and a company $j$, it takes the form of the natural logarithm of one plus the distance. The latter is measured in kilometers using the latitude and longitude of investors' and companies' zip codes. The main explanatory variable, *Post Covid* is a dummy that equals 1 if the financing round happened after February 2020, and zero otherwise. The vector of controls $X$ includes the number of investors participating in the round, the natural logarithm of the round's equity investment amount, and the natural logarithm of the total capital raised by VC funds in the VC's state lagged by one year[14].

As distance between economic agents has been increasing over the past decades as a consequence of advances in storage, computing, and communication technologies (e.g., Petersen and Rajan, 2002), in all our specifications, we include the variable *Time Trend* to correct for the growth in distance (or other analyzed characteristics) between investors and portfolio companies that started before Covid.[15] The specifications also include VC investor fixed effects ($\alpha_i$), investment stage fixed effects ($\gamma_s$), company state $\times$ industry fixed effects ($\eta_{b\times l}$), as well as month ($\omega_m$) fixed effects to control for the seasonality of VC investments.

### 2.3.3 Difference-in-differences approach

To strengthen our analysis and establish a causal relationship between the inability to interact in person and changes in VCs' investment practices, we also follow a difference-in-differences approach. In this setting, we exploit variations in VCs potential ability to switch to online interactions and respond

[14] We control for VC capital raised to ensure that the change in distance is not driven by increased capital chasing limited local investment opportunities (Gompers and Josh Lerner, 2000)

[15] We discuss the historical increase in the distance that can be observed in Figure 2.1 further in the analysis.

to pandemic-related restrictions. The assumption is that VCs that normally used to invest in sectors with remote work feasibility can better adapt to post-pandemic online environment. Given the nature of businesses in these types of industries, such VCs could potentially make online investments even before the pandemic if in-person interactions were not considered essential to collecting soft information. In fact, investing in software or fintech offers the benefit of more effective remote monitoring. In these sectors, the different tasks can be completed remotely with a lower need for in-person interactions, compared to sectors such as biotech or energy that have to rely more on on-site visits and regular face-to-face interactions to successfully complete and monitor more complex tasks.

In addition, VCs familiar with highly remote-workable industries are also more likely to have experienced online interactions before the pandemic. Therefore, we expect such VCs to quickly adapt to this new environment by switching their activity online.

These VCs are more likely to observe an increased set of investment opportunities while learning about their ability to maintain investment activity online. Assuming that soft information collection via in-person interactions was the main barrier to distant investment for VCs typically investing in remote-workable industries, we expect them to seize more distant opportunities after the pandemic. We therefore compare VCs with different exposures to remote work, based on the sectoral composition of their pre-pandemic portfolios as described in section 2.2.

To quantify the causal effect of the shock on in-person interactions in the VC industry, we use the following specification at the VC firm-company-year level:

$$Y_{i,j,t} = \beta_1 WFH\ Exposure_i \times Post\ Covid_t + X'\theta + \alpha_i + \gamma_s + \eta_t + \omega_m + \epsilon_{i,j,t} \tag{2.2}$$

As in equation 2.1, the dependent variable $Y_{i,j,t}$ is the outcome related to the investment made by investor $i$ in company $j$ at time $t$. *Post Covid* is a dummy that equals 1 if the financing round happened after February 2020, and zero otherwise. The main coefficient of interest ($\beta_1$) is for the interaction between *WFH Exposure* and *Post Covid*. The vector of controls $X$ includes the number of investors participating in the round and the natural logarithm of the round's equity investment amount. The specifications include VC firm fixed effects ($\alpha_i$), investment stage fixed effects ($\gamma_s$), year fixed effects ($\eta_t$), as well as month ($\omega_m$) fixed effects to control for the seasonality of VC investments.

To exclude alternative explanations and control for any effect of the Covid-19 on the overall economy or changes in the VC activity that might explain our results, we further restrict our regressions. We sequentially introduce VC state $\times$ year fixed effects and company state $\times$ industry $\times$ year fixed effects. Any time-varying change in a state that might contribute to changes in VCs' investments, such as capital flows or movements of people out or in a state, would be captured by VC state $\times$ year fixed effects. Similarly, any change in the startup's industry and location that might explain the observed changes would be captured by company state $\times$ industry $\times$ year fixed effects.

## 2.4 Investing across usual borders

### 2.4.1 Distance to investments

#### Event-study results

Our results support the idea that the balancing of communication costs between proximate and distant startups made investment opportunities located far away at least as attractive as nearby opportunities, and reveal a significant acceleration of distant investments after the Covid-19 onset. Figure 2.1 shows the evolution of the average distance (in km) between VC firms and their new portfolio companies over time (between 2013 and 2022). As documented in the literature (Petersen and Rajan, 2002), the increase in the average distance between economic agents, such as lenders and borrowers, started decades before the Covid-19 pandemic. In fact, Panel A of Figure 2.1 shows that the distance increase between VC investors and startups was also on the way before Covid: between 2013 and 2019 the average distance grew by 20%. Interestingly, even in the beginning of our observation period, the average distance between a VC and its new portfolio company was nearly 1,100 km, suggesting that investing from far away was not rare. However, the figure suggests the acceleration of the distance growth trend after the pandemic, with Covid fueling distant investments. We also notice an overall persistence of this effect and no mean reversion, with just a slight decrease in the average distance in March-July of 2022 compared to 2021. We observe similar dynamics if we plot only the average distance between lead VC investors and startups in Panel B.

Table 2.2 further confirms these observations by reporting the results of the event-study analysis described by equation 2.1 in Panel A. In all the specifications, the coefficient of *Post Covid* is positive and significant at the 1% level, suggesting a substantial increase in the post-pandemic average distance between VC investors and their portfolio companies, even after adjusting for the trend in distance increase, *Time Trend*. In a cross-section of all investments (columns (1) and (2)), the *Post Covid* coefficient is around 0.30, meaning that the distance between a VC firm and its portfolio company increased on average by 35% post-Covid. If we focus on the distance “within" a VC's portfolio (column (3)), the increase attributed to the Covid-19 is about 20%.

Figure 2.2 complements these results by showing the importance of the changes in terms of distance range. We notice a decrease in deals within a short distance to VC headquarters (<50 km) and an increase in deals at very remote locations (>1,000 km), both at the extensive margins (absolute nb. of deals in Panel A) and at the intensive margins (relative nb. of deals in Panel B).

Next, we test if VCs invest within their own state or if they also became more likely to invest across geographical borders. Panel A of Table 2.2 underlines that VCs are 2.6 to 6.4 percentage points less likely to invest inside their state (columns (4) to (6)), which translates into a 5-12.5% decrease in the unconditional probability.

We also test for the significance of the change in the distance trend slope after the Covid-19 onset. Table 2.15 shows that while the mean distance (the probability of investing in the same state) was increasing (decreasing) before Covid, this trend becomes much steeper post-Covid, irrespective of the starting point of the pre-trend.

### Difference-in-differences results

The difference-in-differences results show that the post-Covid acceleration in distance increase between VC investors and their portfolio companies is primarily driven by VCs more exposed to the remote-work industries before the pandemic. Panel B of Table 2.2 reports a positive and highly statistically significant *WFH Exposure* $\times$ *Post Covid* coefficient in columns (1) to (3), suggesting that VCs with 10% higher exposure to remote work industries are located 12-15% farther away from their portfolio companies after the start of the pandemic. This difference represents a 160 to 200 km increase in the average distance post Covid. This is a significant increase considering that a large proportion of VC deals are made within 50 km distance, as illustrated in Figure 2.2. Columns (4) to (6) also suggest that VCs with a higher exposure to WFH industries are less likely to invest in their own state of location, relative to VCs with lower exposure. These results are robust to including very restrictive fixed effects controlling for the conditions at the VC's location and the startup's location and industry in columns (5) and (6).

As the difference-in-differences method relies on the assumption of parallel trends, in Figure 2.3 we plot the coefficients of interest in a dynamic specification that includes the pre-period. The figure supports that there is no evidence of pre-trend. The coefficients of *WFH Exposure* interacted with time dummies are insignificant in the whole pre-period, with coefficients close to zero in the years before the reference period. Overall, the figure suggests that VCs with lower WFH exposure are an adequate counterfactual group to estimate what would have happened to highly exposed VCs had they not been better equipped to respond to in-person restrictions. Figure 2.5 suggests that the parallel trend assumption is likely to hold for the lead VC investors, and Figure 2.6, confirms that the absence of pre-trend is robust when using a dummy for treatment instead of the continuous *WFH Exposure* variable.

**Alternative explanations and robustness**

While we rely on the impact of the Covid-19 outbreak on soft information transmission to explain our findings, we recognize that the pandemic has significantly affected the overall economy, making other explanations plausible. Therefore, in this section, we describe how we exclude alternative explanations, including pandemic-driven confounding effects, and present several robustness tests to further validate our results.

The increase in distance between a VC investor and a portfolio company might be explained by state-level or industry-level changes that expanded VCs' opportunity set. Indeed, migration from one state to another, changes in the industry composition of a state, or Covid-19-driven industry growth could have contributed to the increase in distant investments. To capture changes in states and industries, we first constrained our difference-in-differences regressions by including VC state $\times$ year and company state $\times$ industry $\times$ year fixed effects and presented the respective results in columns (5) and (6) of Table 2.2 above.

The state-year fixed effects in our difference-in-differences specifications enable us to capture changes in the availability of financial capital at the state levels. Nevertheless, in regressions that do not contain such fixed effects, we control for the venture capital activity through VC funds' inflows to the state. Table 2.14 shows a strong positive long-term relationship between total VC funds' inflows to the state and the average distance to portfolio companies for VCs in this state (the sample period is 2010-2019). As our results hold after controlling for this, the change in distance to investments (and in other investment characteristics presented in the next sections) is unlikely to be driven by abundant capital chasing limited local investment opportunities.[16]

Next, we provide additional evidence that our distance results are not driven by the emergence of new businesses in locations far from typical VC hubs in the post-pandemic period. To do that, in Table 2.16, we restrict our sample to companies that were founded before 2019. The results remain significant for all specifications where the dependent variable is the logarithm of distance, and for most of the regressions with *Same State* outcome variable. Therefore, the relocation of founders after the start of the pandemic from entrepreneurial hubs and the establishment of their companies in distant locations do not drive the observed increase in distance. We also verify that industries that potentially benefited from the pandemic are not explaining our results. Table 2.17 shows that our findings are confirmed even if we exclude companies from industries that could benefit from the pandemic, following the definition by Bellucci et al., 2023. Thus, our results cannot be attributed to VCs chasing pandemic-related companies either.

To further confirm our distance-related findings, we also investigate distances between the startup and its closest VC investor as well as its most remote investor. Table 2.18 shows that the distance between a startup and both its closest and farthest VC increases substantially more post-Covid than it would have increased otherwise (due to *Time Trend*). This result supports our main findings by suggesting that the pandemic contributed to making even the closest investors significantly more distant. Consistent with our difference-in-differences expectations, we also observe that the distance increase to the nearest and farthest VC is relatively more pronounced in deals led by VCs with higher pre-Covid WFH exposure.

Several other tests reported in the Internet Appendix confirm the robustness of our results. Focusing on deals from Lead VC investors only in Table 2.19 does not change our conclusions about distance increase for event-study

[16] The last couple of years were characterized by a boom in venture investing (see for example, data from the National Venture Capital Association 2022 Yearbook: https://nvca.org/wp-content/uploads/2022/03/NVCA-2022-Yearbook-Final.pdf). This was initially driven by the low-interest rate environment that characterized the stock market over the past decade, thus pushing investors to seek higher yields in private markets. To this, the pandemic contributed by forcing governments to increase liquidity in the market.

and difference-in-differences analyses. Table 2.20 also shows results similar to our baseline distance-related findings when restricting our sample to VC investors who have at least 5 deals before and after Covid to make sure that our results are not driven by very small or occasional investors. Our difference-in-differences results for the distance are also robust to using a dummy variable for whether the VC investor has an above-median WFH exposure instead of the continuous measure (Table 2.21) and to excluding VC investors within the top tercile of the WFH exposure measure (Table 2.22).

#### State-level pandemic exposure and distance

So far, in our specifications, we defined the Covid onset using a dummy variable *Post Covid* that is uniformly measured for all investors (it is equal to one if the investment is performed after February, 2020). In order to explore the variation in the severity of the pandemic shock across the U.S. geographies, we supplement our previous analysis with regressions using the differences in the stringency of the governmental social distancing measures, and the number of Covid cases and Covid-related deaths. If the growth of distance between VC investors and portfolio companies is primarily driven by the restriction of in-person interactions, we can expect that those states that experienced a stronger shock from the pandemic, would be more likely to switch to online communications and engage in more remote investments. Similarly, VCs with more previous exposure to high remote-workable industries should better adapt to forced remote interactions and invest in farther away startups.

We obtain data for this analysis using the Oxford COVID-19 Government Response Tracker (Hale et al., 2021). Table 2.12 summarizes the average restrictions captured in the stringency index in several VCs' states from which the largest number of deals in our sample are performed. Note that the variation in the stringency of the social distancing measures across states is somewhat limited, especially among the three states originating the largest number of deals: California, New York, and Massachusetts.[17] However, as Table 2.1 shows, there is a considerable variation in the measure of VC's exposure to WFH industries. It allows us to repeat our distance analysis in Table 2.2 by respectively substituting *Post Covid* variable with a VC's state-level measure of the stringency index, the natural logarithm of the total number of Covid cases, and the natural logarithm of total Covid-related deaths, measured as

[17]This overall similarity in governments' responses across states is a primary reason for choosing *Post Covid* dummy for our main analyses.

monthly averages of respective daily indicators reported by the COVID-19 Government Response Tracker. The continuous nature of these measures allows us to introduce more granular fixed effects. Using interactions with year-month fixed effects instead of a linear time trend or interactions with year fixed effects in the regressions enables us to explore the variation across states in each year-month on the increase in distance. It is important to note that the Stringency Index and the number of cases and deaths are only defined since the start of 2020, therefore the variation for these coefficients' estimates comes from the periods after the pandemic onset, while the pre-pandemic data helps to estimate other regression parameters.

Table 2.3 shows the results of this analysis. In columns (1) to (3), the regressions include company state-industry-year-month and VC investor fixed effects in addition to our usual set of controls. In all of these columns, the coefficients of *Stringency Index*, *Ln(N Covid Cases)*, and *Ln(N Covid Deaths)* are statistically significant, suggesting that there is a significant correlation between the stringency of the lockdown measures or the severity of the effect of Covid in the VC's state and the distance to investments. The *Ln(N Covid Cases)* coefficient's magnitude indicates that with a 100% increase in Covid-related cases, VCs invest in companies 12.8% farther away. The coefficient for the number of Covid-related deaths suggests that a 100% increase in the number of deaths is accompanied by a 15% increase in the distance between VCs and their portfolio companies. It is important to note that the company state-industry-year-month fixed effect controls for the effects of events such as the movement of entrepreneurs in a certain industry to a certain state, or the growth of an industry in a state post-Covid. As a result, these fixed effects help with refuting several alternative explanations for the observed increase in the distance between VCs and their portfolio companies. To further show the robustness of our results, in columns (4) to (6) we present the results following equation 2.2, after replacing the *Post Covid* dummy with the measures of state-level exposure to Covid, or the state-level Covid restrictions. In this specification, we also add VC state-year-month fixed effects, which control for any time-variant change in a state that forces the VCs in that state to invest remotely. Column (4) in Table 2.3 shows that the coefficient on the interaction between VC's WFH exposure and Covid stringency index is positive and significant at the 10% level. In columns (5) and (6) we have a positive coefficient on the interaction term that is significant at 1%. These results show that VCs that had more exposure to industries with more WFH potential invested in more distant startups if their state of location was more severely affected by Covid. Overall, we observe that the severity of Covid impact in a state is associated with an increase in the average distance between VCs and their portfolio companies, supporting the view that the pandemic, indeed, was a strong accelerator of remote VC investments. In addition, the larger increase in distance for VCs with exposure to industries with more WFH potential suggests that online communication may have replaced in-person interactions in deal sourcing, especially in industries where acquiring, collecting, or processing information online is more feasible.

### 2.4.2 Toward a new geographical shape of VC activity?

To get a better sense of the extent to which VCs expanded their geographical horizons after the pandemic, Figure 2.4 displays a state-county level map showing locations of VC investors' portfolio companies before and after Covid. The red color marks counties that received VC financing post-Covid but not in the pre-Covid period (new places for VCs). Light blue-colored counties are places that have been obtaining VC financing since the pre-Covid period (already familiar to VCs). We can observe a growth of investments in regions surrounding the entrepreneurship hubs, plus the appearance of some new areas far away from the usual hubs. However, we do not observe a large number of new investments in new areas.

We further explore, in a regression analysis, whether the post-Covid increase in distance and the emergence of new investment areas far from established entrepreneurial hubs reflect a reallocation of VC investments from the latter towards other locations. If participating in the typical in-hub activities, such as networking events and informal gatherings, had value before the pandemic, we expect entrepreneurial hubs to have lost some of their competitive advantage post-pandemic. Therefore, the probability of investing in a portfolio company located in a hub should be lower post-Covid. We test this in Table 2.4 by focusing on the likelihood of a portfolio company being located in one of the entrepreneurial hubs.[18] While there is no significant difference in the cross-section (columns (1) and (2)), both the event-study and the difference-in-differences analysis reveal a significant change "within" VCs' portfolios. The likelihood of investing in a hub company for a given VC investor fell by 1.6 percentage points post-Covid (column (3)). This represents a 5% decrease in the unconditional probability of investing in a

[18] Entrepreneurial hubs are defined as the top 10 US cities with the largest number of startups before 2020. The list includes: San Francisco, New York, Los Angeles, Boston, Seattle, Palo Alto, Austin, Chicago, Cambridge, and Santa Monica.

hub-based company. Columns (4) to (6) reveal that this change is primarily driven by VCs highly exposed to WFH sectors: a one standard-deviation increase in WFH exposure is associated with a 4.6-5.9% decrease in the likelihood of selecting a hub company. Overall the results show that VCs with high *WFH Exposure*, as hypothesized, are driving investments beyond traditional hubs. These findings raise questions about the future dominance of entrepreneurial hubs: while this shift was already underway, the pandemic may have accelerated this process by motivating some investors to allocate their capital outside these key areas.

## 2.5 Investment characteristics and syndication

### 2.5.1 Changes in investment characteristics

In the previous section, we documented that the Covid restrictions on in-person interactions have led to an increase in distance between VCs and their portfolio companies. Soft information is critically important for investing in startups because of the high information asymmetries between VCs and entrepreneurs (e.g., Tian, 2011). In fact, as the distance between VCs and their portfolio companies increases, VCs try to compensate for the lower possibility of face-to-face meetings and on-site monitoring by investing in more mature companies that can have a longer track record (Sorenson and Stuart, 2001; Sorenson and Stuart, 2008). If videoconferencing doesn't provide VCs with an adequate replacement for face-to-face meetings and monitoring, we expect them to compensate by choosing less risky investment behaviors. This is especially true for VCs who are more likely to encounter difficulties in adapting to online investments due to the nature of their typical investments, i.e. those who were less exposed to WFH industries pre-Covid. On the contrary, we can expect VCs with greater exposure to WFH industries to adapt faster and maintain their activity without significantly changing their investment behaviors, perhaps even increasing their industry scope as they learn about making online investments. Thus, we first explore how VCs leverage their experience to judge investment opportunities in this new environment. Then, we investigate whether and how they might balance the lack of soft information.

We start with testing how VCs leverage their industry expertise by analyzing whether their investments involve VCs that are sector specialists. VC investors tend to specialize in a specific industry since it enables them to accumulate expertise and build a strong network with founders and other professionals working in the same sector (Gompers, Kovner, and Josh Lerner, 2009). This helps them collect valuable information about investment opportunities (Sorenson and Stuart, 2001). Therefore, in the new environment imposed by the pandemic, it might be important to rely on either one's own or others' expertise. In Table 2.5, we study whether post-Covid investments are more likely to involve at least one industry expert. We define a VC as an industry expert if the startup's industry corresponds to the VC's focus industry, that is, the one in which the VC invested the largest amount by the year of the analyzed investment.[19] Our industry focus variable is based on the 40 industry groups classification from Pitchbook.

The event study results show that, both in the cross-section of deals (columns (1) and (2)) and in the "within" VC firm specification (column (3)), a VC is more likely to be a part of a syndicate with at least one company's industry expert. The probability of this happening is 2.1 to 5.3 percentage points higher after Covid. These results suggest a shift toward what can be seen as more prudent behavior. Nevertheless, columns (4) to (6) reveal that this cautious attitude does not come from VCs highly exposed to WFH industries. The *WFH Exposure* $\times$ *Post Covid* interaction coefficients are, indeed, negative and statistically significant at the 1% level. They indicate that a one standard deviation increase in a VC's WFH exposure is associated with approximately 3 percentage points decrease in the likelihood of having an industry expert as part of this VC's investment syndicate after the pandemic.
[20]

In Table 2.6, we explore VCs' adaptation mechanisms further, by looking at the similarity of start-ups selected before and after Covid with previously VC-financed startups. For this test, we compute the Jaccard Similarity[21] score between companies' keyword descriptions reported by Pitchbook. This enables us to obtain the average similarity of a company with respect to other

[19]As Pitchbook does not report the equity investment contributed by each investor, we proxy this amount by dividing the total round size by the number of participating investors.

[20]When it comes to VCs' own expertise, however, Table 2.23 highlights that there is no significant difference between more or less exposed VCs. The results show that post-Covid, VCs are, on average, more likely to invest in companies from their focus industries, irrespective of their exposure to WFH sectors.

[21]Jaccard similarity measures the intersection over the union of sets, unlike cosine similarity, which considers the magnitude of vectors. This makes it particularly suitable in keyword-based analysis, where it provides a more intuitive measure of similarity by focusing solely on the shared elements between sets of keywords.

companies that received early-stage VC financing in the same industry sector during the last three years before the analyzed investment. The event study results show that post-Covid, VCs are more likely to invest in startups that have a higher similarity score with recent-past startups. The coefficients' magnitudes suggest that, on average, startups funded after Covid are 7% more similar to previously funded startups.[22]

However, VCs with higher exposure to WFH industries, again, exhibit less cautious behavior. The interaction coefficient *WFH Exposure* $\times$ *Post Covid* is negative and strongly statistically significant, suggesting that higher WFH-exposure VCs invest in startups with lower similarity to past investments, relative to VCs with lower WFH exposure. In fact, one standard deviation in the WFH exposure is associated with a 3.6 to 4.2% decrease in the similarity score. Thus, only VCs with extremely high exposure to WFH (nearly two standard deviations away from the mean) would invest in startups that are less similar to past investments after Covid. The rest of VCs invest in more similar startups, with similarity being higher when VCs have lower WFH exposure.

Finally, we test if, post-Covid, VCs selected companies that are older. Table 2.7 shows that this is not the case. Columns (1) to (3) indicate that VC investors choose 4 to 6% younger companies for investment after Covid. The interaction coefficients in columns (4) to (6) are not statistically significant, suggesting no significant difference between VCs with higher and lower WFH exposure. In Table 2.24, we further verify whether VCs selected firms that have received earlier financing from accelerators, angels, crowdfunders, etc. We find no evidence that VCs require startups to have pre-VC financing more often.

Thus, the results suggest that VCs do not rely on characteristics that might convey more "hard information", irrespective of VCs' WFH exposure.[23]

[22] The average similarity score in the sample is 3.45, which indicates that the average startup in our sample can be 3.45% similar to the other startups in the same industry in the past three years.

[23] These results could potentially be explained if VCs invested smaller amounts in these younger companies. However, we do not observe any significant change in the investment round sizes after Covid, according to the results in table 2.25.

### 2.5.2 Syndicate formation

The geographical concentration of VCs is closely related to their pre- and post-investment activities: evaluating and monitoring early-stage companies for which little information is available is easier when searching locally (Joshua Lerner, 1995; Sorenson and Stuart, 2001; Bernstein, Giroud, and Townsend, 2016). This is also why networks and syndicates are key when co-investing in distant startups. Multiple and dispersed relationships help not only to learn about potential investment opportunities but also to find co-investors who are closer to distant targets (Sorenson and Stuart, 2001). With the pandemic restrictions, communication channels changed, and finding co-investors became an online activity. In this section, we explore whether VCs changed the way they syndicate after Covid-19.

It is an established fact in the literature that VCs co-invest more under high uncertainty or when information asymmetry is more severe (Bygrave, 1987). Indeed, syndication not only helps to share risk but also enables VCs to bring together more expertise and share information on investment opportunities (Bygrave, 1987; Joshua Lerner, 1994; Brander, Amit, and Antweiler, 2002). Hence, as distance to investments increased after Covid, we might first expect to observe an increase in syndicated deals post-pandemic. On the contrary, as opportunities to casually meet other co-investors and talk about investment opportunities have decreased in the post-pandemic environment, VCs might find it harder to get together with other investors and invest in syndicated deals.

In Table 2.8, we test whether VCs are more or less likely to co-invest with other VCs after the pandemic onset. In Panel A, the event study results support that there is no significant change in the probability of syndicate formation post-Covid. At the same time, results reported in Panel B might indicate that the pandemic made syndicate formation more difficult. Indeed, although VCs are not less likely to syndicate after Covid, the syndicates' size became 4-5% smaller. Regarding the difference-in-differences analysis, the absence of significance for the *WFH Exposure* $\times$ *Post Covid* interaction coefficients in columns (4) to (6) further suggests that this reduction in syndicate size occurred for all VCs, irrespective of their WFH exposure.

To facilitate co-investment coordination and monitoring, VC networks tend to cluster geographically as distance between VCs makes such tasks more challenging (Sorenson and Stuart, 2001). However, with the onset of Covid, we can expect increased distance among syndicate partners for two reasons. First, VCs can reach remote connections in their network to obtain information about investment opportunities in the remote partner's location or simply because the cost of communication with a distant VC became smaller after Covid relative to the cost of communication with a proximate VC. Second, more distant syndicates might result from the focal VC's more distant target company inviting other VCs to join the syndicate. Even if these VCs are close to the company, they will still be far from the focal VC. Thus, we explore whether the geographical distance between syndicate members increased with the pandemic's start in a regression framework.

Table 2.9 focuses on the distance among syndicate members. The dependent variable is defined here as the natural logarithm of the average distance (plus one) between a VC investor and other members of the same syndicate. Columns (1) to (3) show a significant increase in the average distance between a VC and its syndicate members after Covid. In these event study results, the coefficient of *Post Covid* varies between 0.22 and 0.29, translating into a post-covid increase in distance between syndicate partners of 25% to 34%. This is a substantial increase compared to the average growth over time captured by *Time Trend*. Columns (4) to (6) further report the results of the difference-in-differences setting. They reveal that post-Covid, VCs with greater exposure to WFH sectors syndicate with more distant partners, relative to less exposed VCs. This is in line with the assumption that such VCs can more easily adapt to the online environment. Column (4) shows that a one standard deviation increase in *WFH Exposure* reflects a 6.6% increase in the average distance among syndicate partners. The *WFH Exposure* $\times$ *Post Covid* interaction is statistically significant at the 5% level but adding more restrictive fixed effects in columns (5) and (6) progressively reduces the statistical significance - part of the effect is explained by the locations of the VC investor and the startup.

While we document that syndicate partners become more geographically distant after the Covid onset, this raises further questions about the composition of the syndicates. Does this reflect new networks, or do syndicates include more old syndicate partners? We define old syndicate partners as those VCs that co-invested together in the same deal during the three years preceding the year of the analyzed investment. We calculate the proportion of a VC's old syndicate partners in the deal as a sum of all its old syndicate partners divided by the total number of the syndicate members. Columns (1) to (3) from Table 2.10 show that, following the pandemic, VCs participate in syndicates with relatively more of the old partners. The coefficient's magnitude suggests that the proportion of old syndicate partners increases by 3.5-4.4 percentage points, which translates into an approximately 12-15% increase in the old partners' share.

In columns (4) to (6), we do not observe any significant difference between more or less WFH-exposed VCs. The coefficients of the interaction term *WFH Exposure* $\times$ *Post Covid* are negative but insignificant. This absence of difference highlights the importance of relying on old partners to adapt to new conditions regardless of VCs' flexibility.

Overall, the results in this section suggest that, while VCs rely on smaller syndicates post-pandemic, they prefer to partner with their old connections. At the same time, they also reach more distant co-investors. In line with the observed increase in distance between VCs and their portfolio companies, VCs highly exposed to WFH industries are also those partnering more with distant investors. These results reflect the need to gather more information on distant startups (more distant co-investors) and to mitigate higher information uncertainty by reaching a trusted network (higher proportion of old partners). These findings are potentially as powerful as the first set of results on distance to investments in terms of implications for the geography of entrepreneurship, as new ways of collaboration among VCs can change the traditional information diffusion.

We also investigate (in Section 2.11 of the Internet Appendix) whether online deal sourcing leads to worse performance of investments. More specifically, we study the probability of receiving the second round of VC financing within 12 and 18 months after the first round and the probability of exits via IPO or M&A within 18 months of the first VC financing. Our findings indicate that the probability of getting a second round of financing or exiting fast did not decrease for investments made after the Covid-19, irrespective of the VCs' exposure to the remote-work industries.

## 2.6 Conclusion

VC investors have traditionally perceived in-person interactions as highly valuable for making investment decisions. However, the arrival of Covid-19 challenged this norm by replacing face-to-face communication with online meetings. We use this unique setting created by the pandemic to test the validity of the VC investment model based on in-person interactions and to explore changes in VCs' behavior when they switch to online communication.

We establish that VCs broke their proximity culture and broadened their geographical horizons. At the same time, our results reveal that online interactions do not seem to perfectly substitute for in-person meetings. Indeed, VCs balance the lack of soft information with their own expertise and choose businesses that are more similar to past investments. We also show that the VCs' syndication process is affected by this new environment. Post-Covid, VCs rely more on their existing network and syndicates include members that are, on average, more distant from each other.

Overall, our findings show that VCs change their investment behavior as a result of the inability to meet startup founders in-person and visit their offices. Nevertheless, they make only careful steps, and our results suggest that in-person interactions are still relevant for VCs. This careful approach in a new environment is not surprising considering their investment style, as explained by Roelof Botha's view about online fundraising: *"The risk, in my mind, especially at the earlier stages, is that you're not just raising money, you're recruiting a business partner. You're recruiting an investor who's going to be with you on a journey"*.[24]

This view is supported by several interviews that we conducted with VC practitioners. Investors state that the pandemic showed them that online meetings could provide sufficient information to make an investment decision, but there are caveats. Online investments are easier to process at earlier stages and for relatively small investment cheques. Also, as highlighted in our empirical strategy, practitioners stress that some industries might be more suitable for online fundraising. Considering that in-person visits do not generate substantial advantages in some cases, investors expect a hybrid form of investment to remain in the future. Finally, VCs also emphasized that opportunities for distant investments often came via their network. Thus, these insights from practitioners confirm our results on the heterogeneity of distance change across the VC and deal types, the increasing role of networks, as well as the persistence of distant investments.

Our results have important implications for VC investors and the geographical spread of entrepreneurial activity. If using online communication technologies for VC deal sourcing persists, it can have important implications for the growth of high-quality entrepreneurial activities and employment outside the VC hubs. Overall, this study is also likely to have important

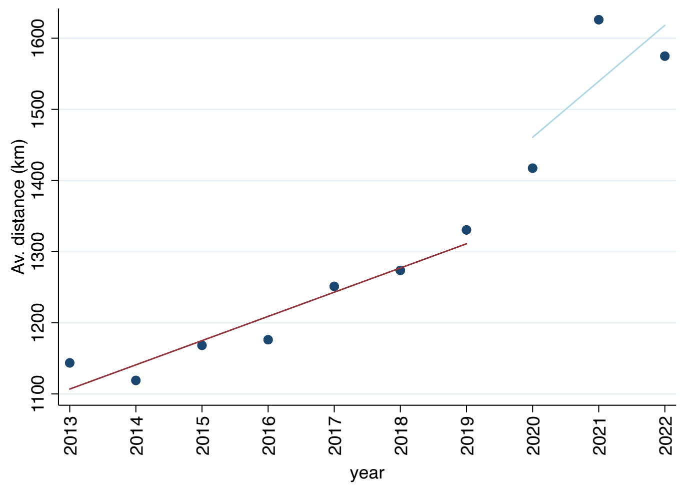
[24]Roelof Botha is the Sequoia partner we referred to in the introduction. From *McKinsey on startups* podcast. See https://www.mckinsey.com/industries/technology-media-and-telecommunications/our-insights/global-vc-view-funding-startups-in-the-next-normal.

implications for other industries that rely on soft information for financing decisions.

## 2.7 Figures and Tables

FIGURE 2.1: **Average Distance Over Time.** The plot shows the average distance (in km) between all VC firms and their new portfolio companies over the years in Panel A, and between Lead VC firms and their portfolio companies in Panel B. The sample covers companies that received their first investment round between March 2013 and July 2022 and defined as “seed" and “early stage".

**Panel A. All VC firms.**




**Panel B. Lead VC firms.**

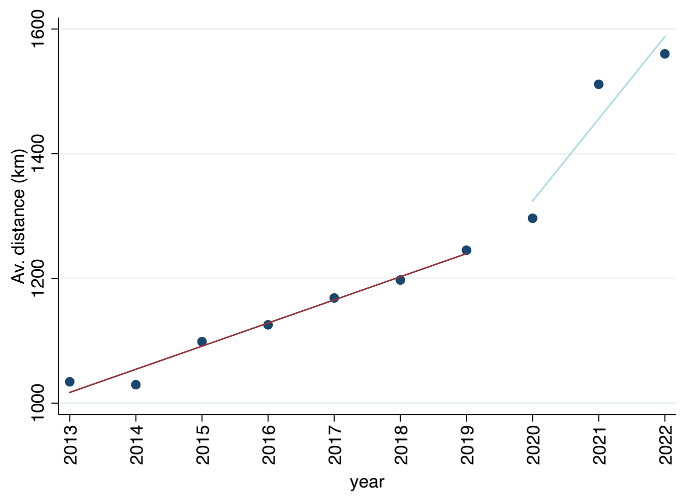
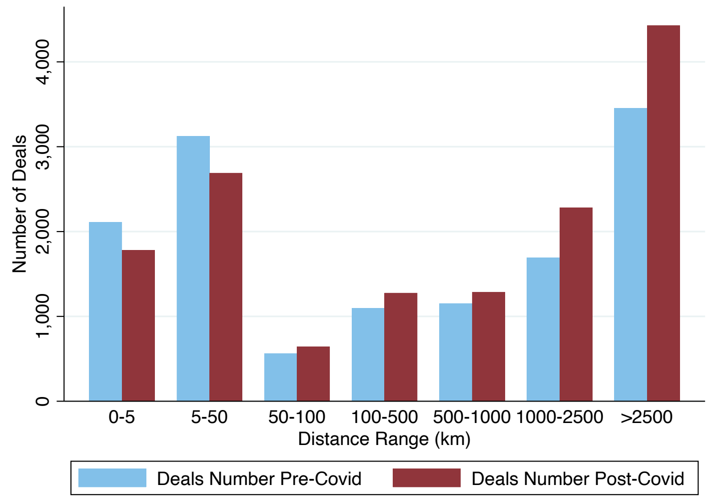


FIGURE 2.2: **Change in Distribution of Deals by Distance.** The figure reports the number of deals (Panel A) and the shares of deals (Panel B) pre and post-Covid, by different distance ranges (in km). The pre-Covid period is October 2017 - February 2020, and the post-Covid period is March 2020 - July 2022 (equal number of months before and after the Covid onset).

**Panel A. Number of Deals.**




**Panel B. Share of Deals.**

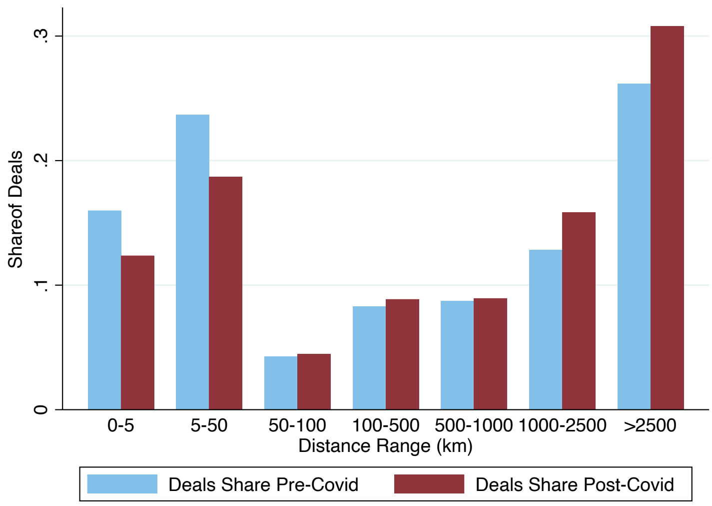


FIGURE 2.3: **Difference-in-Differences Estimates for Distance.** The figure plots the estimated coefficients for the interaction terms of each year dummy and the $WFH\ Exposure$ variable in an OLS regression. The dependent variable, $Y_{ijt}$, is the natural logarithm of one plus the distance between a VC investor and a portfolio company. Regressions include VC firm, year, month and round fixed effects. Standard errors are clustered at the VC firm level. The sample covers companies that received their first investment between March 2013 and July 2022 and defined as “seed" and “early stage". The unit of observation is the portfolio company-VC investor pair. The year 2019, preceding the pandemic, is the excluded category. The vertical lines represent 95% confidence intervals.

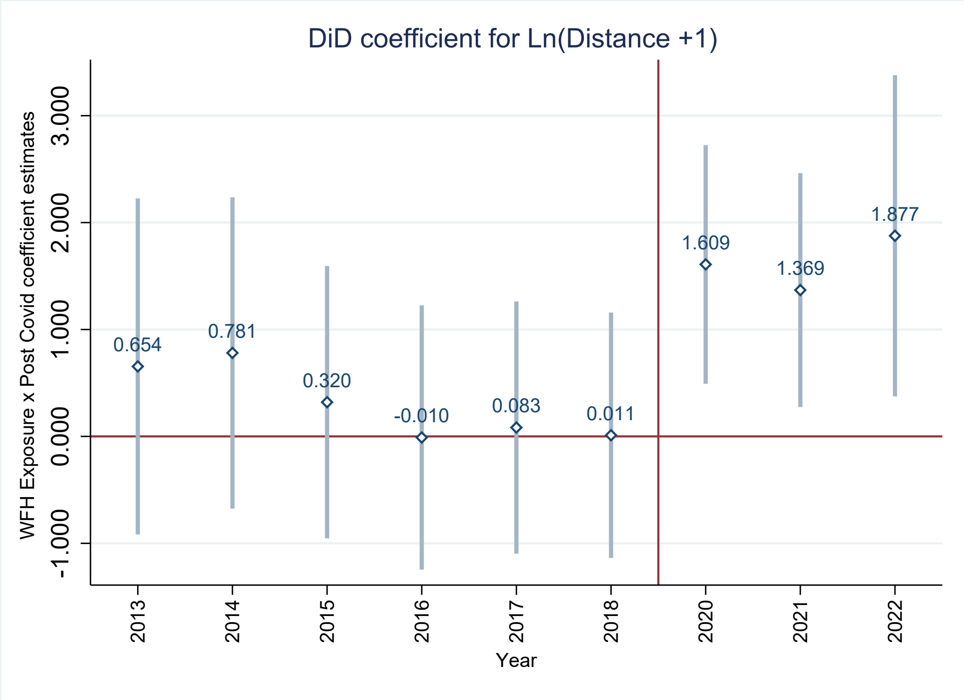


FIGURE 2.4: **New Geographies Post-Covid.** The figure reports a county level map showing the location of portfolio companies of VC investors before and after Covid. The red color marks counties that received VC financing after Covid but not in the analyzed pre-Covid period. Light blue-colored counties had already obtained VC financing pre-Covid. The pre-Covid period is March 2013 - February 2020, and the post-Covid period is March 2020 - July 2022.

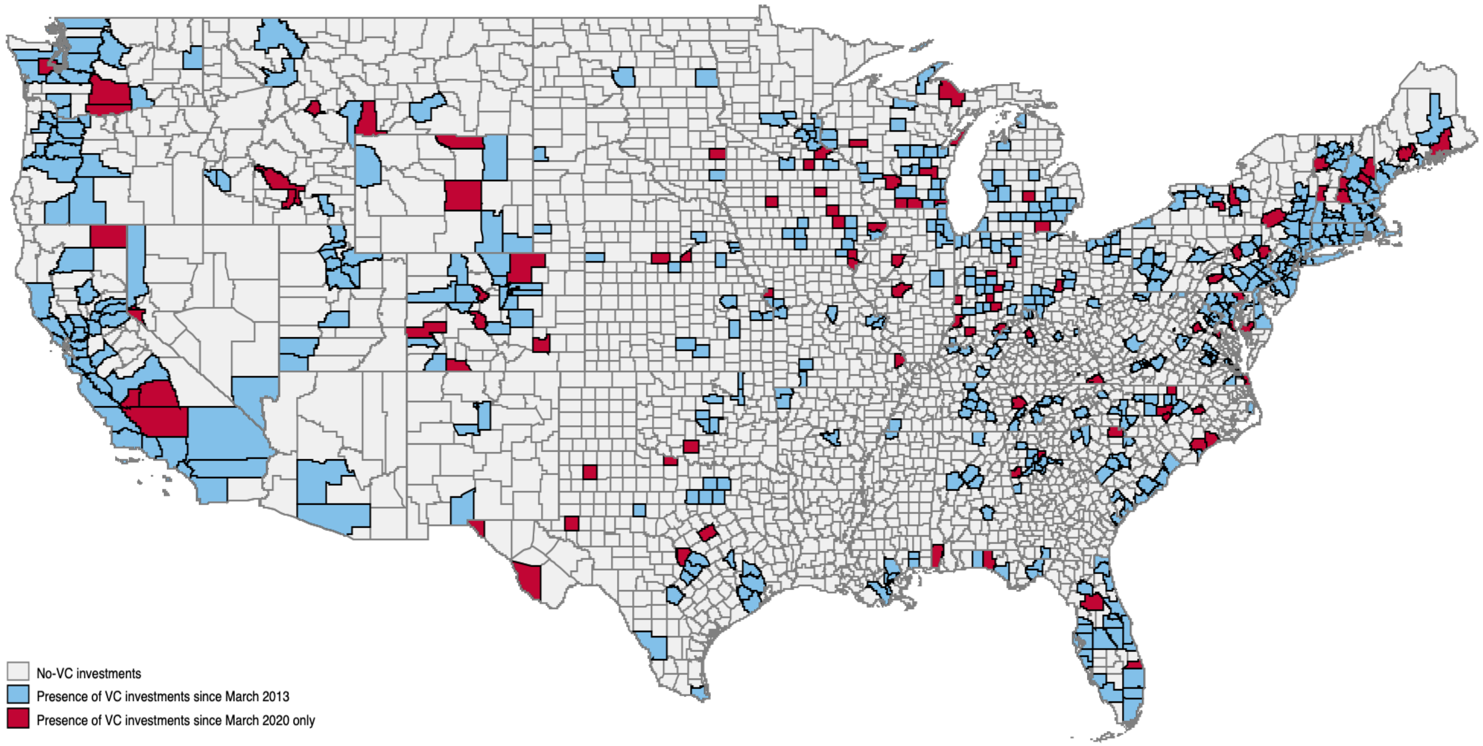


TABLE 2.1: **Descriptive Statistics.** The table reports the descriptive statistics for the main variables used in the analysis. Statistics are reported at deal characteristics with the unit of observation at the portfolio company-VC investor pair level. The dataset includes the first investment round received by a U.S. company between March, 2013, and July, 2022 and defined as “seed”or “early stage”.

| | **N Obs** | **Mean** | **Std. Dev.** | **Min** | **Median** | **Max** |
|---|---|---|---|---|---|---|
| Distance (km) | 46,652 | 1,318 | 1,635 | 0 | 326 | 7,940 |
| Ln(Distance+1) | 46,652 | 5.17 | 2.74 | 0 | 5.79 | 8.98 |
| P(Same State) | 46,652 | 0.51 | 0.50 | 0 | 1.00 | 1.00 |
| Hub company | 46,652 | 0.49 | 0.50 | 0 | 0.00 | 1.00 |
| Syndicated deal | 46,652 | 0.81 | 0.40 | 0 | 1.00 | 1.00 |
| Round’s N VCs | 46,652 | 3.86 | 2.76 | 1.00 | 3.00 | 28 |
| Round Equity ($ mil, deflated) | 46,652 | 7.35 | 26.45 | 0.00 | 3.02 | 2586 |
| Ln(Round Equity) | 46,652 | 1.06 | 1.37 | -6.92 | 1.11 | 7.86 |
| Company Age | 46,056 | 2.99 | 1.69 | 1 | 3.00 | 10.00 |
| P(Seed Round) | 46,652 | 0.64 | 0.48 | 0 | 1.00 | 1.00 |
| P(Pre-VC Financing) | 46,652 | 0.28 | 0.45 | 0 | 0.00 | 1.00 |
| Similarity Score | 46,604 | 3.45 | 1.76 | 0 | 3.29 | 11.66 |
| VC’s WFH Exposure | 44,994 | 0.51 | 0.09 | 0.04 | 0.52 | 0.83 |
| Av. Distance within Syndicate (km) | 37,609 | 1,583 | 1,298 | 0 | 1,421 | 8,183 |
| Ln(Av. Distance within Syndicate) | 37,609 | 6.44 | 2.03 | 0 | 7.26 | 9.01 |
| Proportion of Old Syndicate Partners | 37,608 | 0.29 | 0.35 | 0 | 0.17 | 1.00 |
| Startup in VCs’ Focus Industry | 46,652 | 0.55 | 0.50 | 0 | 1.00 | 1.00 |

TABLE 2.2: **Post-Covid Distance to Investments.** The table reports the results from OLS regressions following equation 2.1 in Panel A, and 2.2 in Panel B. The dependent variable is: in columns (1) to (3), the natural logarithm of one plus distance between the VC investor and the startup that received financing; and in columns (4) to (6), a dummy variable equal to one if the portfolio company is located in the VC's state and zero otherwise. The regression dataset includes the first investment round received by a company between March, 2013, and July, 2022, and defined as "seed" or "early stage". The unit of observation is the portfolio company-VC investor pair. Controls include a natural logarithm of the round's equity investment and the number of investors participating in the round in all specifications, and the natural logarithm of the total capital raised by VC funds in the VC's state lagged by one year in specifications without VC State × Year fixed effects. Standard errors are clustered at the VC investor level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

**Panel A. Event study**

| | Ln(Distance+1) | | | P(Same State) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Post Covid | 0.300*** | 0.290*** | 0.185*** | -0.064*** | -0.056*** | -0.026*** |
| | (0.051) | (0.050) | (0.042) | (0.009) | (0.009) | (0.007) |
| Time Trend | 0.096*** | 0.077*** | 0.060*** | -0.017*** | -0.011*** | -0.007*** |
| | (0.012) | (0.012) | (0.009) | (0.002) | (0.002) | (0.002) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Company State × Industry FE | | ✓ | ✓ | | ✓ | ✓ |
| VC FE | | | ✓ | | | ✓ |
| Observations | 46,321 | 46,286 | 45,087 | 46,321 | 46,286 | 45,087 |
| R-squared | 0.024 | 0.080 | 0.308 | 0.054 | 0.198 | 0.438 |

**Panel B. Difference-in-differences**

| | Ln(Distance+1) | | | P(Same State) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| WFH Exposure × Post Covid | 1.397*** | 1.303*** | 1.131*** | -0.160** | -0.143** | -0.125** |
| | (0.370) | (0.375) | (0.388) | (0.065) | (0.066) | (0.063) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| VC FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | | | ✓ | | |
| VC State × Year FE | | ✓ | ✓ | | ✓ | ✓ |
| Company State × Industry × Year FE | | | ✓ | | | ✓ |
| Observations | 43,879 | 44,147 | 43,760 | 43,879 | 44,147 | 43,760 |
| R-squared | 0.246 | 0.254 | 0.333 | 0.299 | 0.309 | 0.468 |

TABLE 2.3: **Post-Covid Distance to Investments - by VCs' State Exposure to Covid.** The table reports the results of an OLS regression where the dependent variable is the natural logarithm of one plus the distance between the VC investor and the startup that received financing. The regression dataset includes the first investment round received by a company between March, 2013, and July, 2022, and defined as "seed" or "early stage". The unit of observation is the portfolio company-VC investor pair. In all specifications, controls include a natural logarithm of the round's equity investment, the number of investors participating in the round, and the natural logarithm of the total capital raised by VC funds in the VC's state lagged by one year in specifications without VC State × Year fixed effects. *Stringency Index* is measured at the state of the VC's headquarters location and is estimated as a monthly average of Covid-related measures' Stringency Index in the Oxford COVID-19 Government Response Tracker (Hale et al., 2021). *Ln(N Cases)* is a natural logarithm of the average monthly confirmed number of total Covid cases. *Ln(N Deaths)* is a natural logarithm of the average monthly confirmed number of total deaths from Covid. All measures at the state level are lagged by one month with respect to the month of the analyzed deal to ensure a time lag between the change in the state's exposure and VCs' decisions about investments. In columns (4) to (6), the main independent variable is interacted with a measure of exposure to remote work sectors based on the VC's portfolio companies before the pandemic, as defined in Section 2.3. Standard errors are clustered at the VC's state and year-month level. *** p<0.01, ** p<0.05, * p<0.1.

| | Ln(Distance+1) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Stringency Index | 0.018*** | | | | | |
| | (0.005) | | | | | |
| Ln(N Covid Cases) | | 0.128** | | | | |
| | | (0.051) | | | | |
| Ln(N Covid Deaths) | | | 0.150*** | | | |
| | | | (0.018) | | | |
| WFH Exposure X Stringency Index | | | | 0.016* | | |
| | | | | (0.008) | | |
| WFH Exposure X Ln(N Covid Cases) | | | | | 0.079*** | |
| | | | | | (0.023) | |
| WFH Exposure X Ln(N Covid Deaths) | | | | | | 0.111*** |
| | | | | | | (0.031) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| VC FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Company State x Industry x Year FE x Month | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| VC State x Year FE x Month | | | | ✓ | ✓ | ✓ |
| Observations | 42,639 | 42,639 | 42,639 | 40,711 | 40,711 | 40,711 |
| R-squared | 0.395 | 0.395 | 0.395 | 0.447 | 0.447 | 0.447 |

TABLE 2.4: **Post-Covid Startups' Location.** The table reports the results from OLS regressions following equation 2.1 in columns (1) to (3), and 2.2 in columns (4) to (6). The dependent variable is a dummy variable for whether the company is located in one of the entrepreneurial hubs. Entrepreneurial hubs are defined as the top 10 US cities with the largest number of startups before 2020. The regression dataset includes the first investment round received by a company between March, 2013, and July, 2022, and defined as "seed"or "early stage". The unit of observation is the portfolio company-VC investor pair. Controls include a natural logarithm of the round's equity investment and the number of investors participating in the round in all specifications, and the natural logarithm of the total capital raised by VC funds in the VC's state lagged by one year in specifications without VC State × Year fixed effects. Standard errors are clustered at the VC investor level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

| | P(Hub Company) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Post Covid | -0.011 | -0.012 | -0.016** | | | |
| | (0.002) | (0.008) | (0.008) | | | |
| Time Trend | -0.015*** | -0.014*** | -0.008*** | | | |
| | (0.002) | (0.002) | (0.002) | | | |
| WFH Exposure × Post Covid | | | | -0.194*** | -0.210** | -0.165** |
| | | | | (0.062) | (0.064) | (0.066) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Company Industry FE | | ✓ | ✓ | | | |
| VC FE | | | ✓ | ✓ | ✓ | ✓ |
| Year FE | | | | ✓ | | |
| VC State × Year FE | | | | | ✓ | ✓ |
| Company Industry × Year FE | | | | | | ✓ |
| Observations | 46,321 | 46,316 | 45,121 | 43,879 | 44,147 | 44,142 |
| R-squared | 0.073 | 0.083 | 0.231 | 0.227 | 0.232 | 0.239 |

TABLE 2.5: **Probability of Syndicate VCs' Investing in Focus Industry.** The table reports the results from OLS regressions following equation 2.1 in columns (1) to (3), and 2.2 in columns (4) to (6). The dependent variable is a dummy variable equal to one if the portfolio company comes from the focus industry of at least one VC participating in the round of investment. The unit of observation is at the portfolio company-VC level. The VC's focus industry is one of 40 primary industry groups reported by Pitchbook, in which the VC invested the largest amount in the last 3 years. The regression dataset includes the first investment round received by a company between March, 2013, and July, 2022, and defined as "seed"or "early stage". Controls include a natural logarithm of the round's equity investment and the number of investors participating in the round in all specifications, and the natural logarithm of the total capital raised by VC funds in the VC's state lagged by one year in specifications without VC State × Year fixed effects. Standard errors are clustered at the VC investor level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

| | P(Startup in VCs' Focus Industry) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Post Covid | 0.053*** | 0.023*** | 0.021*** | | | |
| | (0.008) | (0.007) | (0.007) | | | |
| Time Trend | -0.004** | 0.001 | 0.004*** | | | |
| | (0.002) | (0.001) | (0.001) | | | |
| WFH Exposure × Post Covid | | | | -0.315*** | -0.331*** | -0.288*** |
| | | | | (0.068) | (0.068) | (0.064) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Company State × Industry FE | | ✓ | ✓ | | | |
| VC FE | | | ✓ | ✓ | ✓ | ✓ |
| Year FE | | | | ✓ | | |
| VC State × Year FE | | | | | ✓ | ✓ |
| Company State × Industry × Year FE | | | | | | ✓ |
| Observations | 46,321 | 46,286 | 45,087 | 43,879 | 44,147 | 43,760 |
| R-squared | 0.045 | 0.423 | 0.514 | 0.164 | 0.173 | 0.559 |

TABLE 2.6: **Startup Similarity to Past Investments.** The table reports the results from OLS regressions following equation 2.1 in columns (1) to (3), and 2.2 in columns (4) to (6). The dependent variable is an average similarity of the company with respect to other companies that received early-stage VC financing in the same industry during three years before the analyzed deal. The pairwise similarity score is estimated using companies' keyword descriptions (unique words only) reported by Pitchbook. The results are robust to using word combinations to compute the similarity instead. The regression dataset includes the first investment round received by a company between March, 2013, and July, 2022 and defined as "seed" or "early round". The unit of observation is the portfolio company-VC investor pair. Controls include a natural logarithm of the round's equity investment and the number of investors participating in the round in all specifications, and the natural logarithm of the total capital raised by VC funds in the VC's state lagged by one year in specifications without VC State × Year fixed effects. Standard errors are clustered at the VC investor level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

| | Past Similarity Score | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Post Covid | 0.245*** | 0.265*** | 0.243*** | | | |
| | (0.027) | (0.026) | (0.028) | | | |
| Time Trend | 0.008 | -0.011** | -0.009 | | | |
| | (0.005) | (0.005) | (0.006) | | | |
| WFH Exposure × Post Covid | | | | -1.522*** | -1.626*** | -1.361*** |
| | | | | (0.233) | (0.237) | (0.221) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Company State × Industry FE | | ✓ | ✓ | | | |
| VC FE | | | ✓ | ✓ | ✓ | ✓ |
| Year FE | | | | ✓ | | |
| VC State × Year FE | | | | | ✓ | ✓ |
| Company State × Industry × Year FE | | | | | | ✓ |
| Observations | 46,273 | 46,243 | 45,046 | 43,834 | 44,102 | 43,721 |
| R-squared | 0.023 | 0.185 | 0.251 | 0.133 | 0.142 | 0.323 |

TABLE 2.7: **Company characteristics: Age.** The table reports the results from OLS regressions following equation 2.1 in columns (1) to (3), and 2.2 in columns (4) to (6). The dependent variable is the portfolio company's age (winsorized at 1 and 99 percent). The regression dataset includes the first investment round received by a company between March, 2013, and July, 2022 and defined as "seed", or "early round". The unit of observation is the portfolio company-VC investor pair. Controls include a natural logarithm of the round's equity investment and the number of investors participating in the round in all specifications, and a measure for the local venture capital availability defined as the natural logarithm of the total capital raised by VC funds in the VC's state lagged by one year in specifications without VC State × Year fixed effects. Standard errors are clustered at the VC investor level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

| | Company's Age | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Post Covid | -0.179*** | -0.159*** | -0.125*** | | | |
| | (0.030) | (0.029) | (0.030) | | | |
| Time Trend | 0.099*** | 0.088*** | 0.080*** | | | |
| | (0.005) | (0.005) | (0.007) | | | |
| WFH Exposure × Post Covid | | | | 0.091 | 0.130 | 0.281 |
| | | | | (0.254) | (0.243) | (0.244) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Company State × Industry FE | | ✓ | ✓ | | | |
| VC FE | | | ✓ | ✓ | ✓ | ✓ |
| Year FE | | | | ✓ | | |
| VC State × Year FE | | | | | ✓ | ✓ |
| Company State × Industry × Year FE | | | | | | ✓ |
| Observations | 45,731 | 45,696 | 44,501 | 43,310 | 43,572 | 43,187 |
| R-squared | 0.053 | 0.096 | 0.225 | 0.193 | 0.207 | 0.296 |

TABLE 2.8: **Probability of Deal Syndication and Number of VCs per Round.** The table reports the results from OLS regressions following equation 2.1 in columns (1) to (3), and 2.2 in columns (4) to (6). The dependent variable is: a dummy equal to one if the deal is syndicated (Panel A), and the natural logarithm of the number of VCs in the syndicate (Panel B). The regression dataset includes the first investment round received by a company between March, 2013 and July, 2022 and defined as "seed" or "early round", Panel B only include deals with at least two VC investors. The unit of observation is the portfolio company-VC investor pair. Controls include a natural logarithm of the round's equity investment in all specifications, and a measure for the local venture capital availability defined as the natural logarithm of the total VC capital raised in the state of the lead VC investor lagged by one year in specifications without VC State × Year fixed effects. Standard errors are clustered at the VC investor level. *** p<0.01, ** p<0.05, * p<0.1. Panel B follows on the next page.

**Panel A. Probability of Deal Syndication**

| | P(Syndicated Deal) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Post Covid | -0.010 | -0.010 | -0.012* | | | |
| | (0.006) | (0.006) | (0.006) | | | |
| Time Trend | -0.005*** | -0.002* | -0.001 | | | |
| | (0.001) | (0.001) | (0.001) | | | |
| WFH Exposure × Post Covid | | | | -0.051 | -0.009 | 0.001 |
| | | | | (0.053) | (0.052) | (0.055) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Company State × Industry FE | | ✓ | ✓ | | | |
| VC FE | | | ✓ | ✓ | ✓ | ✓ |
| Year FE | | | | ✓ | | |
| VC State × Year FE | | | | | ✓ | ✓ |
| Company State × Industry × Year FE | | | | | | ✓ |
| Observations | 46,321 | 46,286 | 45,087 | 43,879 | 44,147 | 43,760 |
| R-squared | 0.121 | 0.149 | 0.297 | 0.279 | 0.289 | 0.338 |

**Panel B. Syndicate Size**

| | Ln(Round N. of VCs) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Post Covid | -0.048*** | -0.043*** | -0.039*** | | | |
| | (0.010) | (0.009) | (0.010) | | | |
| Time Trend | -0.009*** | -0.006*** | -0.009*** | | | |
| | (0.002) | (0.002) | (0.002) | | | |
| WFH Exposure × Post Covid | | | | -0.104 | -0.067 | -0.033 |
| | | | | (0.074) | (0.074) | (0.078) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Company State × Industry FE | | ✓ | ✓ | | | |
| VC FE | | | ✓ | ✓ | ✓ | ✓ |
| Year FE | | | | ✓ | | |
| VC State × Year FE | | | | | ✓ | ✓ |
| Company State × Industry × Year FE | | | | | | ✓ |
| Observations | 37,330 | 37,327 | 36,235 | 35,317 | 35,539 | 35,490 |
| R-squared | 0.098 | 0.142 | 0.264 | 0.239 | 0.249 | 0.339 |

TABLE 2.9: **Distance Among Syndicate Members.** The table reports the results from OLS regressions following equation 2.1 in columns (1) to (3), and 2.2 in columns (4) to (6). The dependent variable is the natural logarithm of one plus average distance between each VC and other VCs in the syndicate. The regression dataset includes the first investment round received by a company between March, 2013, and July, 2022 and defined as "seed" or "early round", deals that have only one VC investor are excluded. The unit of observation is the portfolio company-VC investor pair. Controls include a natural logarithm of the round's equity investment and the number of investors participating in the round in all specifications, and a measure for the local venture capital availability defined as the natural logarithm of the total VC capital raised in the state of the VC investor lagged by one year in specifications without VC State × Year fixed effects. Standard errors are clustered at the VC investor level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

| | Ln(Average Distance within Syndicate +1) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Post Covid | 0.285*** | 0.290*** | 0.223*** | | | |
| | (0.037) | (0.037) | (0.038) | | | |
| Time Trend | 0.054*** | 0.050*** | 0.037*** | | | |
| | (0.008) | (0.008) | (0.009) | | | |
| WFH Exposure × Post Covid | | | | 0.707** | 0.582* | 0.508 |
| | | | | (0.299) | (0.302) | (0.309) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Company State × Industry FE | | ✓ | ✓ | | | |
| VC FE | | | ✓ | ✓ | ✓ | ✓ |
| Year FE | | | | ✓ | | |
| VC State × Year FE | | | | | ✓ | ✓ |
| Company State × Industry × Year FE | | | | | | ✓ |
| Observations | 37,329 | 37,326 | 36,234 | 35,316 | 35,538 | 35,489 |
| R-squared | 0.086 | 0.128 | 0.278 | 0.257 | 0.267 | 0.331 |

TABLE 2.10: **Average Proportion of Old Syndicate Partners.** The table reports the results from OLS regressions following equation 2.1 in columns (1) to (3), and 2.2 in columns (4) to (6). The dependent variable is the proportion of VCs' old syndicate partners in the round. Old syndicate partners are those VCs who co-invested together with the focal VC during three years preceding the year of the analyzed investment. The proportion of the VC's old syndicate partners in the deal is a sum of all pairs in which the VC has an old partner divided by the total number of pairs this VC forms in the syndicate. The regression dataset includes the first investment round received by a company between March, 2013, and July, 2022 and defined as "seed" or "early round", deals that have only one VC investor are excluded. The unit of observation is the portfolio company-VC investor pair. Controls include a natural logarithm of the round's equity investment and the number of investors participating in the round in all specifications, and a measure for the local venture capital availability defined as the natural logarithm of the total VC capital raised in the state of the VC investor lagged by one year in specifications without VC State × Year fixed effects. Standard errors are clustered at the VC investor level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

| | Proportion of Old Syndicate Partners | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Post Covid | 0.041*** | 0.044*** | 0.035*** | | | |
| | (0.011) | (0.011) | (0.009) | | | |
| Time Trend | -0.011*** | -0.011*** | 0.005*** | | | |
| | (0.002) | (0.002) | (0.002) | | | |
| WFH Exposure × Post Covid | | | | -0.090 | -0.050 | -0.060 |
| | | | | (0.071) | (0.060) | (0.062) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Company State × Industry FE | | ✓ | ✓ | | | |
| VC FE | | | ✓ | ✓ | ✓ | ✓ |
| Year FE | | | | ✓ | | |
| VC State × Year FE | | | | | ✓ | ✓ |
| Company State × Industry × Year FE | | | | | | ✓ |
| Observations | 37,328 | 37,325 | 36,233 | 35,315 | 35,537 | 35,488 |
| R-squared | 0.013 | 0.040 | 0.321 | 0.301 | 0.316 | 0.375 |

## 2.8 Appendix

TABLE 2.11: **Variables Definition**. The Table describes the main variables used in the analysis.

| Variable Name | Definition |
|---|---|
| Ln(Distance+1) | Natural logarithm of one plus distance between the VC investor and the startup that received financing. Distance is measured in kilometers using the latitude and longitude of investors' and companies' zip codes. |
| P(Same State) | Indicator variable equaling one if the portfolio company is located in the VC's state and zero otherwise. |
| Post Covid | Indicator variable equaling one if the financing round happened after February 2020 and zero otherwise. |
| Time Trend | A linear time trend to capture the general trend in the dependent variable. |
| WFH Exposure | The weighted average of industry-level measure of work-from-home feasibility for each VC's portfolio before the pandemic. Deal sizes are used as weights. |
| Stringency Index | A measure of level of Covid-19 restrictions in the state of the VC's headquarter location. This measure is estimated as a monthly average of Covid-related measures' Stringency Index in the Oxford COVID-19 Government Response Tracker (Hale et al., 2021). This measure is lagged by one month with respect to the month of the analyzed deal. |
| Ln(N Covid Cases) | Natural logarithm of the average monthly confirmed number of total Covid cases. This measure is lagged by one month with respect to the month of the analyzed deal. |
| Ln(N Covid Deaths) | Natural logarithm of the average monthly confirmed number of total deaths from Covid. This measure is lagged by one month with respect to the month of the analyzed deal. |
| Hub Company | Indicator variable for whether the portfolio company is located in one of the entrepreneurial hubs. Entrepreneurial hubs are defined as the top 10 US cities with the largest number of startups before 2020. |
| P(Startup in VCs' Focus Industry) | Indicator variable equaling one if the portfolio company comes from the focus industry of at least one VC participating in the round of investment. |
| Past Similarity Score | Average similarity of the company with respect to other companies that received early-stage VC financing in the same industry during three years before the analyzed deal. The pairwise similarity score is estimated using companies' keyword descriptions (unique words only) reported by Pitchbook. |
| Company's Age | Portfolio company's age (winsorized at 1 and 99 percent). |
| P(Had Pre-VC Financing) | Indicator variable for having a financing round (from accelerators, angels, crowdfunding, etc.) before receiving the first VC financing. |

## 2.9 Internet Appendix

FIGURE 2.5: **Difference-in-Differences Estimates for Distance - Lead VC.** The figure plots the estimated coefficients for the interaction terms of each year dummy and the *WFH Exposure* variable in an OLS regression. The unit of observation is adjusted to portfolio company-lead VC investor pair. The dependent variable, $Y_{ijt}$, is the natural logarithm of one plus the distance between a VC investor and a portfolio company. Regressions include VC firm, year, month and round fixed effects. The sample covers companies that received their first investment between March 2013 and July 2022 and defined as "seed" and "early stage". The year 2019, preceding the pandemic start, is the excluded category. The vertical lines represent 95% confidence intervals.

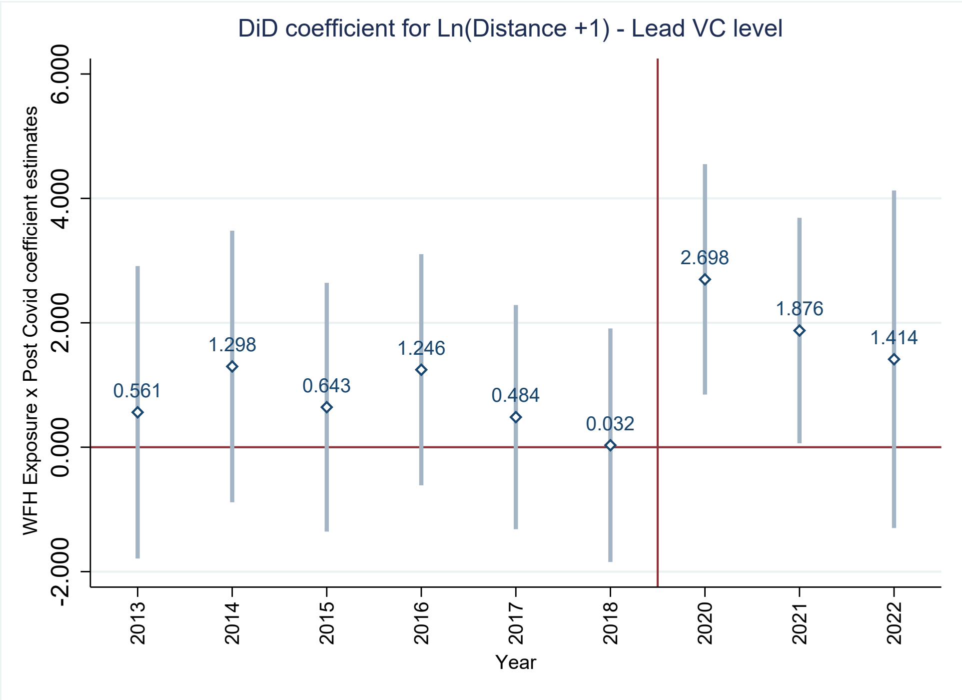


FIGURE 2.6: **Difference-in-Differences Estimates for Distance - High WFH VCs.** The figure plots the estimated coefficients for the interaction terms of each year dummy and the *High WFH VC* dummy variable (equal to one if the VC's *WFH Exposure* is above the median level) in an OLS regression. The dependent variable, $Y_{ijt}$, is the natural logarithm of one plus the distance between a VC investor and a portfolio company. Regressions include VC firm, year, month and round fixed effects. The sample covers companies that received their first investment between March 2013 and July 2022 and defined as "seed" and "early stage". The year 2019, preceding the pandemic start, is the excluded category. The vertical lines represent 95% confidence intervals.

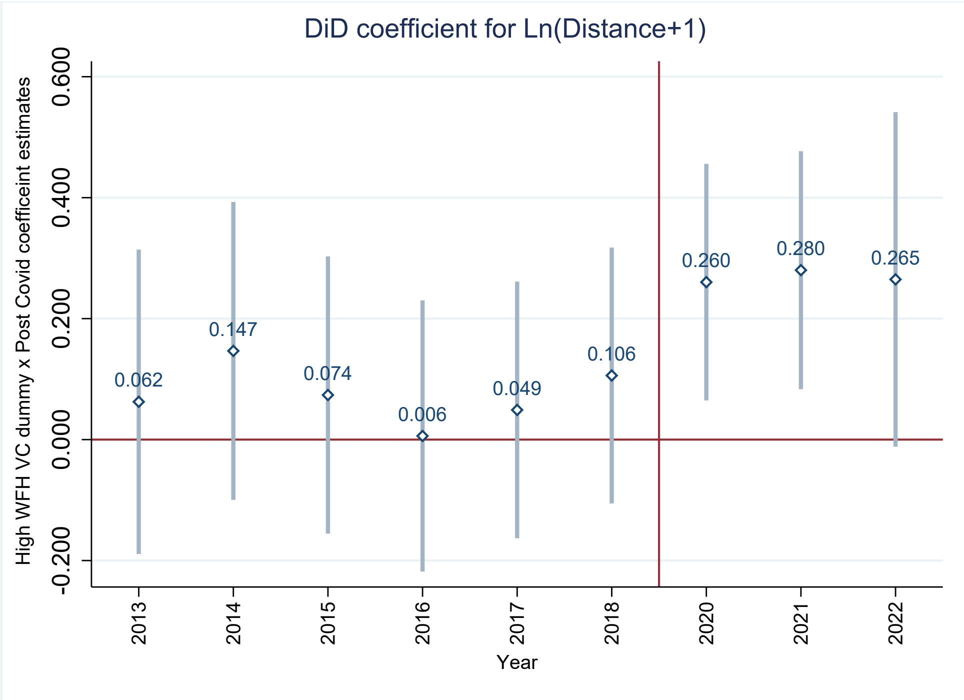


TABLE 2.12: **Stringency of Covid-related Restrictions by State.** The table reports the monthly average of Covid-related measures' Stringency Index estimated using the data from the Oxford COVID-19 Government Response Tracker (Hale et al., 2021). The reported state is the state of the VC headquarters location. The table only reports the Index for the top-10 U.S. states in terms of the number of deals in which VCs from these states participate in our sample (VCs from the top-10 states participate in 84% of all deals in our sample, with VCs from the top-3 states participating in nearly 70% of all deals).

| | Calendar Year and Month | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 2020 | | | | | | | | | | | |
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| California | 1.3 | 8.1 | 46.6 | 76.9 | 65.4 | 62.0 | 62.0 | 60.4 | 58.8 | 56.4 | 55.6 | 60.8 |
| New York | 1.5 | 8.3 | 48.7 | 79.6 | 77.2 | 70.5 | 70.9 | 70.2 | 69.4 | 69.8 | 70.2 | 69.9 |
| Massachusetts | - | - | 31.5 | 67.6 | 66.3 | 59.7 | 60.2 | 59.3 | 57.4 | 50.9 | 58.2 | 65.5 |
| Texas | 0.4 | 2.8 | 28.4 | 71.7 | 62.0 | 45.2 | 53.2 | 52.5 | 48.0 | 46.4 | 49.9 | 48.2 |
| Illinois | 0.7 | 4.8 | 32.8 | 71.9 | 73.4 | 57.1 | 44.0 | 43.0 | 44.0 | 46.0 | 50.2 | 54.6 |
| Colorado | - | 0.6 | 31.0 | 75.2 | 67.9 | 58.4 | 52.8 | 48.3 | 44.5 | 42.1 | 42.1 | 42.1 |
| Washington | - | 0.2 | 35.7 | 65.7 | 61.1 | 50.2 | 48.6 | 51.4 | 51.4 | 51.4 | 57.6 | 63.0 |
| Pennsylvania | - | 5.9 | 34.5 | 74.0 | 65.4 | 45.7 | 45.0 | 49.3 | 47.1 | 41.9 | 46.8 | 60.6 |
| Maryland | - | - | 38.1 | 87.0 | 84.2 | 66.8 | 56.0 | 50.7 | 47.7 | 44.6 | 52.3 | 57.5 |
| Florida | - | 1.0 | 40.0 | 73.3 | 68.0 | 62.4 | 65.0 | 51.8 | 46.4 | 25.6 | 23.6 | 29.1 |
| | 2021 | | | | | | | | | | | |
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| California | 60.8 | 58.8 | 56.5 | 56.6 | 53.8 | 43.2 | 32.4 | 30.4 | 30.6 | 32.2 | 34.3 | 29.8 |
| New York | 66.7 | 64.6 | 57.7 | 44.0 | 38.2 | 36.4 | 31.5 | 32.4 | 31.9 | 30.6 | 30.6 | 30.6 |
| Massachusetts | 68.6 | 65.7 | 60.8 | 57.2 | 53.8 | 21.7 | 19.7 | 22.2 | 22.2 | 22.2 | 22.2 | 22.2 |
| Texas | 47.6 | 45.4 | 38.5 | 35.7 | 30.3 | 24.1 | 24.7 | 25.9 | 28.6 | 29.5 | 28.3 | 18.3 |
| Illinois | 55.6 | 47.2 | 46.3 | 45.8 | 44.4 | 29.4 | 17.7 | 19.4 | 19.4 | 19.4 | 19.4 | 19.4 |
| Colorado | 44.4 | 40.5 | 40.3 | 34.3 | 28.2 | 28.2 | 19.9 | 18.7 | 21.3 | 21.3 | 21.3 | 21.3 |
| Washington | 63.0 | 60.2 | 55.6 | 55.6 | 51.7 | 43.1 | 32.4 | 32.4 | 33.0 | 38.0 | 38.0 | 38.0 |
| Pennsylvania | 52.7 | 51.9 | 29.6 | 28.6 | 28.1 | 13.7 | 11.1 | 11.1 | 13.5 | 14.6 | 15.8 | 16.4 |
| Maryland | 56.5 | 50.0 | 45.5 | 43.5 | 31.5 | 20.4 | 18.8 | 15.7 | 16.7 | 16.7 | 16.7 | 13.9 |
| Florida | 33.4 | 31.9 | 36.6 | 35.9 | 9.5 | 8.3 | 8.9 | 11.1 | 12.4 | 11.1 | 13.0 | 11.1 |
| | 2022 | | | | | | | | | | | |
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| California | 31.0 | 26.6 | 24.2 | 20.4 | 20.4 | 20.4 | 20.4 | - | - | - | - | - |
| New York | 31.8 | 32.4 | 29.4 | 28.7 | 20.9 | 20.2 | 18.5 | - | - | - | - | - |
| Massachusetts | 25.3 | 27.8 | 22.2 | 18.7 | 16.7 | 16.7 | 16.7 | - | - | - | - | - |
| Texas | 11.6 | 11.1 | 11.1 | 11.1 | 11.1 | 11.1 | 11.1 | - | - | - | - | - |
| Illinois | 19.4 | 19.4 | 19.4 | 19.4 | 19.4 | 19.4 | 19.4 | - | - | - | - | - |
| Colorado | 21.3 | 16.7 | 16.7 | 16.7 | 17.3 | 16.7 | 16.7 | - | - | - | - | - |
| Washington | 36.3 | 36.1 | 22.2 | 22.2 | 22.2 | 19.1 | 16.7 | - | - | - | - | - |
| Pennsylvania | 19.2 | 16.8 | 16.7 | 16.7 | 16.7 | 16.7 | 16.7 | - | - | - | - | - |
| Maryland | 14.5 | 16.7 | 16.7 | 16.7 | 16.7 | 16.7 | 16.7 | - | - | - | - | - |
| Florida | 16.0 | 18.3 | 20.4 | 20.4 | 19.3 | 16.7 | 11.1 | - | - | - | - | - |

TABLE 2.13: **Average Score of Remote Work Feasibility by Industry Group.** The table reports the average WFH score for the Pitchbook industry groups. The score for each group is estimated by first matching Pitchbook's detailed industry codes (186 categories) to NAICS industries based on their descriptions and then calculating the average score across industry codes within the industry group (40 categories). Only top-20 industry groups sorted by the number of deals in our data are reported in the table.

| Industry Group | Average WFH Score |
|---|---|
| Restaurants, Hotels and Leisure | 12.8% |
| Transportation | 17.4% |
| Retail | 17.5% |
| Healthcare Services | 27.7% |
| Consumer Durables | 28.4% |
| Consumer Non-Durables | 28.5% |
| Apparel and Accessories | 29.7% |
| Healthcare Devices and Supplies | 29.7% |
| Commercial Products | 32.6% |
| Computer Hardware | 32.6% |
| Pharmaceuticals and Biotechnology | 38.9% |
| Communications and Networking | 44.3% |
| Healthcare Technology Systems | 49.4% |
| Software | 59.6% |
| Media | 65.4% |
| Commercial Services | 69.5% |
| Services (Non-Financial) | 70.5% |
| Other Financial Services | 76.1% |
| Insurance | 76.2% |
| IT Services | 80.3% |

TABLE 2.14: **VC Fundraising and Distance to Investments - Long-Term Analysis.** The table reports the results of an OLS regression where the dependent variable is: in columns (1) and (2), the natural logarithm of the average distance between the VC investor and its portfolio company plus one, where the average is estimated across all deals satisfying the below criteria in a VC's state-year; in columns (3) and (4), an average probability that a VC's portfolio company in located outside the VC's headquarters state, where the average is calculated across all deals satisfying the below criteria in a VC's state-year. The regression dataset includes VC investment rounds received by companies between 2000 and 2019 and defined as "seed or "early stage". The independent variables are: in columns (1) and (3), the natural logarithm of total VC capital raised by U.S. funds headquartered in the state each year (deflated) as reported by Refinitiv's *Amount Raised* variable and in columns (2) and (4), the natural logarithm of total size of funds headquartered in the state by vintage year (deflated) as reported by Refinitiv's *Fund Size* variable. Fundraising data from Refinitiv in this analysis covers the period of 2010-2019. All measures of fundraising are lagged by one year. The unit of observation is U.S. state-year. All regressions include the VC state fixed effects. All regressions are weighted by the number of deals in the state-year. Standard errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

| | Ln(Distance+1) | | P(Same State) | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Ln(Total Funds Raised) | 0.029*** | | -0.011** | |
| | (0.010) | | (0.005) | |
| Ln(Total Funds Size) | | 0.030** | | -0.013** |
| | | (0.012) | | (0.005) |
| VC State FE | ✓ | ✓ | ✓ | ✓ |
| Observations | 837 | 843 | 837 | 843 |
| R-squared | 0.592 | 0.593 | 0.831 | 0.832 |

TABLE 2.15: **Post-Covid Distance to Investments - Change in Trend.** The table reports the results of an OLS regression where the dependent variable is: in columns (1), (2), (5), and (6), the natural logarithm of one plus the distance between the VC investor and the startup that received financing; and in columns (3), (4), (7), and (8), a dummy variable equal to one if the portfolio company is located in the VC's state and zero otherwise. The regression dataset includes the first investment round received by a company and defined as "seed" or "early stage", either from March 2013 to July 2022 (columns (1)-(4)) or from March 2016 to July 2022 (columns (5)-(8)). *Time Trend*, defined as in previous regressions, is a linear time trend over the whole observation period; *Time Post* is a linear time trend in the post-Covid period and it equals zero before Covid; *Post Covid* is a dummy equal to one if the investment occurred since March, 2020 and zero otherwise. The unit of observation is the portfolio company-VC investor pair. In all specifications, controls include a natural logarithm of the round's equity investment, the number of investors participating in the round, and the natural logarithm of the total capital raised by VC funds in the VC's state lagged by one year. Standard errors are clustered at the VC investor level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

| | Since 2013 | | | | Since 2016 | | | |
|---|---|---|---|---|---|---|---|---|
| | Ln(Distance+1) | | P(Same State) | | Ln(Distance+1) | | P(Same State) | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Time Trend | 0.071*** | 0.055*** | -0.010*** | -0.006*** | 0.079*** | 0.080*** | -0.011*** | -0.009*** |
| | (0.012) | (0.010) | (0.002) | (0.002) | (0.021) | (0.018) | (0.004) | (0.003) |
| Time Post | 0.121*** | 0.106*** | -0.022*** | -0.016*** | 0.124*** | 0.106*** | -0.024*** | -0.017*** |
| | (0.037) | (0.034) | (0.006) | (0.006) | (0.040) | (0.037) | (0.007) | (0.006) |
| Post Covid | 0.107 | 0.031 | -0.022* | -0.003 | 0.078 | -0.020 | -0.019 | 0.003 |
| | (0.071) | (0.063) | (0.012) | (0.010) | (0.073) | (0.066) | (0.012) | (0.011) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Company State × Industry FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| VC FE | | ✓ | | ✓ | | ✓ | | ✓ |
| Observations | 46,286 | 45,087 | 46,286 | 45,087 | 34,593 | 33,515 | 34,593 | 33,515 |
| R-squared | 0.081 | 0.308 | 0.198 | 0.438 | 0.083 | 0.322 | 0.207 | 0.453 |

TABLE 2.16: **Post-Covid Distance to Investments - Robustness with Companies Founded Before 2019.** The table corresponds to Table 2.2 restricted to companies founded before 2019. It reports the results from OLS regressions following equation 2.1 in Panel A, and 2.2 in Panel B. The dependent variable is: in columns (1) to (3), the natural logarithm of one plus distance between the VC investor and the startup that received financing; and in columns (4) to (6), a dummy variable equal to one if the portfolio company is located in the VC's state and zero otherwise. The regression dataset includes the first investment round received between March, 2013, and July, 2022, and defined as "seed" or "early stage". The unit of observation is the portfolio company-VC investor pair. Controls include a natural logarithm of the round's equity investment and the number of investors participating in the round in all specifications, and the natural logarithm of the total capital raised by VC funds in the VC's state lagged by one year in specifications without VC State × Year fixed effects. Standard errors are clustered at the VC investor level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

**Panel A. Event study**

| | Ln(Distance+1) | | | P(Same State) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Post Covid | 0.294*** | 0.257*** | 0.200*** | -0.074*** | -0.055*** | -0.038*** |
| | (0.059) | (0.059) | (0.054) | (0.011) | (0.010) | (0.009) |
| Time Trend | 0.095*** | 0.077*** | 0.059*** | -0.016*** | -0.011*** | -0.006*** |
| | (0.012) | (0.012) | (0.010) | (0.002) | (0.002) | (0.002) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Company State × Industry FE | | ✓ | ✓ | | ✓ | ✓ |
| VC FE | | | ✓ | | | ✓ |
| Observations | 35,703 | 35,665 | 34,473 | 35,703 | 35,665 | 34,473 |
| R-squared | 0.018 | 0.072 | 0.313 | 0.048 | 0.186 | 0.438 |

**Panel B. Difference-in-differences**

| | Ln(Distance+1) | | | P(Same State) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| WFH Exposure × Post Covid | 1.830*** | 1.694*** | 1.811*** | -0.193** | -0.156 | -0.173* |
| | (0.515) | (0.522) | (0.543) | (0.093) | (0.095) | (0.093) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| VC FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | | | ✓ | | |
| VC State × Year FE | | ✓ | ✓ | | ✓ | ✓ |
| Company State × Industry × Year FE | | | ✓ | | | ✓ |
| Observations | 34,210 | 34,419 | 34,027 | 34,210 | 34,419 | 34,027 |
| R-squared | 0.258 | 0.268 | 0.344 | 0.313 | 0.325 | 0.474 |

TABLE 2.17: **Post-Covid Distance to Investments - Robustness to Excluding Pandemic-related Companies.** The table corresponds to Table 2.2 excluding companies defined as “pandemic-related" following Bellucci et al., 2023. It reports the results from OLS regressions following equation 2.1 in Panel A, and 2.2 in Panel B. The dependent variable is: in columns (1) to (3), the natural logarithm of one plus distance between the VC investor and the startup that received financing; and in columns (4) to (6), a dummy variable equal to one if the portfolio company is located in the VC’s state and zero otherwise. The regression dataset includes the first investment round received between March, 2013, and July, 2022, and defined as “seed” or “early stage”. The unit of observation is the portfolio company-VC investor pair. Controls include a natural logarithm of the round’s equity investment and the number of investors participating in the round in all specifications, and the natural logarithm of the total capital raised by VC funds in the VC’s state lagged by one year in specifications without VC State × Year fixed effects. Standard errors are clustered at the VC investor level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

**Panel A. Event study**

| | Ln(Distance+1) | | | P(Same State) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Post Covid | 0.371*** | 0.355*** | 0.237*** | -0.067*** | -0.062*** | -0.031*** |
| | (0.066) | (0.065) | (0.060) | (0.012) | (0.011) | (0.010) |
| Time Trend | 0.085*** | 0.062*** | 0.054*** | -0.016*** | -0.009*** | -0.006*** |
| | (0.014) | (0.014) | (0.012) | (0.003) | (0.002) | (0.002) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Company State × Industry FE | | ✓ | ✓ | | ✓ | ✓ |
| VC FE | | | ✓ | | | ✓ |
| Observations | 24,768 | 24,722 | 23,684 | 24,768 | 24,722 | 23,684 |
| R-squared | 0.027 | 0.089 | 0.329 | 0.061 | 0.218 | 0.469 |

**Panel B. Difference-in-differences**

| | Ln(Distance+1) | | | P(Same State) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| WFH Exposure × Post Covid | 1.762*** | 1.582*** | 1.526*** | -0.266*** | -0.237** | -0.227** |
| | (0.525) | (0.545) | (0.553) | (0.095) | (0.098) | (0.091) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| VC FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | | | ✓ | | |
| VC State × Year FE | | ✓ | ✓ | | ✓ | ✓ |
| Company State × Industry × Year FE | | | ✓ | | | ✓ |
| Observations | 23,132 | 23,251 | 22,922 | 23,132 | 23,251 | 22,922 |
| R-squared | 0.256 | 0.268 | 0.360 | 0.313 | 0.326 | 0.506 |

TABLE 2.18: **Post-Covid Minimum and Maximum Distance to Investments.** The table reports the results from OLS regressions following equation 2.1 in columns (1) to (3), and 2.2 in columns (4) to (6). The dependent variable is the natural logarithm of one plus distance between the startup and its most proximate VC investor (Panel A) and the natural logarithm of one plus distance between the startup and its most remote VC investor (Panel B). The regression dataset includes the first investment round received by a company between March, 2013, and July, 2022, and defined as "seed" or "early stage". The unit of observation is the portfolio company-lead VC pair. Controls include a natural logarithm of the round's equity investment and the number of investors participating in the round in all specifications, and the natural logarithm of the total capital raised by VC funds in the VC's state lagged by one year in specifications without VC State × Year fixed effects. Standard errors are clustered at the VC investor level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Panel B follows on the next page.

**Panel A. Distance between startup and closest VC investor**

| | Ln(Minimum Distance+1) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Post Covid | 0.287*** | 0.265*** | 0.231*** | | | |
| | (0.070) | (0.067) | (0.067) | | | |
| Time Trend | 0.087*** | 0.066*** | 0.047*** | | | |
| | (0.013) | (0.012) | (0.012) | | | |
| WFH Exposure × Post Covid | | | | 1.654*** | 1.923*** | 1.139* |
| | | | | (0.611) | (0.652) | (0.651) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Company State × Industry FE | | ✓ | ✓ | | | |
| VC FE | | | ✓ | ✓ | ✓ | ✓ |
| Year FE | | | | ✓ | | |
| VC State × Year FE | | | | | ✓ | ✓ |
| Company State × Industry × Year FE | | | | | | ✓ |
| Observations | 19,665 | 19,623 | 18,416 | 18,204 | 18,282 | 17,684 |
| R-squared | 0.112 | 0.190 | 0.383 | 0.306 | 0.319 | 0.431 |

**Panel B. Distance between startup and most distant VC investor**

| | Ln(Maximum Distance+1) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Post Covid | 0.265*** | 0.252*** | 0.210*** | | | |
| | (0.066) | (0.064) | (0.062) | | | |
| Time Trend | 0.065*** | 0.056*** | 0.057*** | | | |
| | (0.013) | (0.012) | (0.012) | | | |
| WFH Exposure × Post Covid | | | | 1.624*** | 1.695*** | 1.606*** |
| | | | | (0.518) | (0.544) | (0.569) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Company State × Industry FE | | ✓ | ✓ | | | |
| VC FE | | | ✓ | ✓ | ✓ | ✓ |
| Year FE | | | | ✓ | | |
| VC State × Year FE | | | | | ✓ | ✓ |
| Company State × Industry × Year FE | | | | | | ✓ |
| Observations | 19,665 | 19,623 | 18,416 | 18,204 | 18,282 | 17,684 |
| R-squared | 0.160 | 0.210 | 0.417 | 0.377 | 0.390 | 0.460 |

TABLE 2.19: **Post-Covid Distance to Investments - Lead VC.** The table reports the results from OLS regressions following equation 2.1 in columns (1) to (3), and 2.2 in columns (4) to (6) with the unit of observation at the portfolio company - Lead VC investor pair. The dependent variable is the natural logarithm of one plus the distance between the lead VC investor and the startup (Panel A) and a dummy variable equal to one if the portfolio company is located in the VC's state and zero otherwise (Panel B). The regression dataset includes the first investment round received by a company between March, 2013, and July, 2022 and defined as "seed" or "early stage". Controls include a natural logarithm of the round's equity investment and the number of investors participating in the round in all specifications, and the natural logarithm of the total capital raised by VC funds in the VC's state lagged by one year in specifications without VC State × Year fixed effects. Standard errors are clustered at the Lead VC investor level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Panel B follows on the next page.

**Panel A. Distance to Portfolio Company**

| | Ln(Distance+1) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Post Covid | 0.253*** | 0.225*** | 0.167** | | | |
| | (0.077) | (0.075) | (0.067) | | | |
| Time Trend | 0.084*** | 0.068*** | 0.053*** | | | |
| | (0.015) | (0.014) | (0.013) | | | |
| WFH Exposure × Post Covid | | | | 1.721*** | 1.779*** | 1.640** |
| | | | | (0.579) | (0.617) | (0.671) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Company State × Industry FE | | ✓ | ✓ | | | |
| VC FE | | | ✓ | ✓ | ✓ | ✓ |
| Year FE | | | | ✓ | | |
| VC State × Year FE | | | | | ✓ | ✓ |
| Company State × Industry × Year FE | | | | | | ✓ |
| Observations | 19,665 | 19,623 | 18,416 | 18,204 | 18,282 | 17,684 |
| R-squared | 0.020 | 0.085 | 0.363 | 0.299 | 0.312 | 0.409 |

**Panel B. VC and Startup in the Same State**

| | P(Same State) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Post Covid | -0.056*** | -0.044*** | -0.022** | | | |
| | (0.014) | (0.013) | (0.011) | | | |
| Time Trend | -0.014*** | -0.010*** | -0.006*** | | | |
| | (0.003) | (0.003) | (0.002) | | | |
| WFH Exposure × Post Covid | | | | -0.224** | -0.233** | -0.228** |
| | | | | (0.101) | (0.109) | (0.111) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Company State × Industry FE | | ✓ | ✓ | | | |
| VC FE | | | ✓ | ✓ | ✓ | ✓ |
| Year FE | | | | ✓ | | |
| VC State × Year FE | | | | | ✓ | ✓ |
| Company State × Industry × Year FE | | | | | | ✓ |
| Observations | 19,665 | 19,623 | 18,416 | 18,204 | 18,282 | 17,684 |
| R-squared | 0.030 | 0.184 | 0.481 | 0.342 | 0.356 | 0.533 |

TABLE 2.20: **Post-Covid Distance to Investments - Robustness to Nb of Deals.** The table reports the results from OLS regressions following equation 2.1 in Panel A, and 2.2 in Panel B, with data restricted to VCs with at least 5 deals before and after Covid.. The dependent variable is: in columns (1) to (3), the natural logarithm of one plus the distance between the VC investor and the startup that received financing; and in columns (4) to (6), a dummy variable equal to one if the portfolio company is located in the VC's state and zero otherwise. The regression dataset includes the first investment round received by a company between March, 2013, and July, 2022 and defined as "seed"or "early stage". The unit of observation is the portfolio company-VC investor pair. Controls include a natural logarithm of the round's equity investment and the number of investors participating in the round in all specifications, and the natural logarithm of the total capital raised by VC funds in the VC's state lagged by one year in specifications without VC State × Year fixed effects. Standard errors are clustered at the VC investor level. *** p<0.01, ** p<0.05, * p<0.1.

**Panel A. Event study**

| | Ln(Distance+1) | | | P(Same State) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Post Covid | 0.243*** | 0.255*** | 0.179*** | -0.051*** | -0.050*** | -0.030*** |
| | (0.066) | (0.063) | (0.050) | (0.012) | (0.011) | (0.008) |
| Time Trend | 0.101*** | 0.071*** | 0.065*** | -0.017*** | -0.009*** | -0.006*** |
| | (0.017) | (0.017) | (0.012) | (0.003) | (0.003) | (0.002) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Company State × Industry FE | | ✓ | ✓ | | ✓ | ✓ |
| VC FE | | | ✓ | | | ✓ |
| Observations | 27,721 | 27,687 | 27,687 | 27,721 | 27,687 | 27,687 |
| R-squared | 0.023 | 0.098 | 0.281 | 0.057 | 0.246 | 0.440 |

**Panel B. Difference-in-differences**

| | Ln(Distance+1) | | | P(Same State) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| WFH Exposure × Post Covid | 1.770*** | 1.600*** | 1.215** | -0.215** | -0.174* | -0.115 |
| | (0.549) | (0.565) | (0.565) | (0.094) | (0.099) | (0.091) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| VC FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | | | ✓ | | |
| VC State × Year FE | | ✓ | ✓ | | ✓ | ✓ |
| Company State × Industry × Year FE | | | ✓ | | | ✓ |
| Observations | 27,721 | 27,878 | 27,542 | 27,721 | 27,878 | 27,542 |
| R-squared | 0.203 | 0.213 | 0.313 | 0.266 | 0.277 | 0.472 |

TABLE 2.21: **Post-Covid Distance to Investments (Diff-in-Diff) - Robustness to High WFH Exposure Dummy.** The table reports the results of Panel B in Table 2.2 when replacing the continuous measure of WFH Exposure by a dummy variable. The dependent variable is: in columns (1) to (3), the natural logarithm of one plus distance between the VC investor and the startup that received financing; and in columns (4) to (6), a dummy variable equal to one if the portfolio company is located in the VC's state and zero otherwise. *High WFH VC* is a dummy variable equal to one if the *WFH Exposure* of the VC is above the median value in 2019 and zero otherwise. The regression dataset includes the first investment round received by a company between March, 2013, and July, 2022, and defined as "seed" or "early stage". The unit of observation is the portfolio company-VC investor pair. Controls include a natural logarithm of the round's equity investment and the number of investors participating in the round in all specifications, and the natural logarithm of the total capital raised by VC funds in the VC's state lagged by one year in specifications without VC State × Year fixed effects. Standard errors are clustered at the VC investor level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

| | Ln(Distance+1) | | | P(Same State) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| High WFH VC × Post Covid | 0.213*** | 0.195*** | 0.149** | -0.029** | -0.025** | -0.017 |
| | (0.067) | (0.065) | (0.065) | (0.011) | (0.011) | (0.010) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| VC FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | | | ✓ | | |
| VC State × Year FE | | ✓ | ✓ | | ✓ | ✓ |
| Company State × Industry × Year FE | | | ✓ | | | ✓ |
| Observations | 43,879 | 44,147 | 43,760 | 43,879 | 44,147 | 43,760 |
| R-squared | 0.246 | 0.254 | 0.333 | 0.299 | 0.309 | 0.468 |

TABLE 2.22: **Post-Covid Distance to Investments (Diff-in-Diff) - Robustness to excluding VCs with High WFH Exposure.** The table reports the results of Panel B in Table 2.2 when excluding VC investors from the top tercile of the WFH Exposure. The dependent variable is: in columns (1) to (3), the natural logarithm of one plus distance between the VC investor and the startup that received financing; and in columns (4) to (6), a dummy variable equal to one if the portfolio company is located in the VC's state and zero otherwise. The regression dataset includes the first investment round received by a company between March, 2013, and July, 2022, and defined as "seed" or "early stage", but excludes VC investors from the top tercile of the WFH Exposure. The unit of observation is the portfolio company-VC investor pair. Controls include a natural logarithm of the round's equity investment and the number of investors participating in the round in all specifications, and the natural logarithm of the total capital raised by VC funds in the VC's state lagged by one year in specifications without VC State × Year fixed effects. Standard errors are clustered at the VC investor level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

| | Ln(Distance+1) | | | P(Same State) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| WFH Exposure × Post Covid | 1.237*** | 1.152** | 1.093** | -0.098 | -0.082 | -0.093 |
| | (0.475) | (0.475) | (0.488) | (0.083) | (0.084) | (0.079) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| VC FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | | | ✓ | | |
| VC State × Year FE | | ✓ | ✓ | | ✓ | ✓ |
| Company State × Industry × Year FE | | | ✓ | | | ✓ |
| Observations | 36,891 | 37,099 | 36,672 | 36,891 | 37,099 | 36,672 |
| R-squared | 0.246 | 0.254 | 0.337 | 0.304 | 0.314 | 0.478 |

TABLE 2.23: **Probability of Investing in Focus Industry.** The table reports the results from OLS regressions following equation 2.1 in columns (1) to (3), and 2.2 in columns (4) to (6). The dependent variable is a dummy variable equal to one if the portfolio company comes from the VC's focus industry. The unit of observation is the company-VC investor pair. The VC's focus industry is one of 40 primary industry groups reported by Pitchbook, in which the VC invested the largest amount in the last 3 years. The regression dataset includes the first investment round received by a company between March, 2013, and July, 2022, and defined as "seed"or "early stage". Controls include a natural logarithm of the round's equity investment and the number of investors participating in the round in all specifications, and the natural logarithm of the total capital raised by VC funds in the VC's state lagged by one year in specifications without VC State × Year fixed effects. Standard errors are clustered at the VC investor level. *** p<0.01, ** p<0.05, * p<0.1.

| | P(Startup in VC's Focus Industry) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Post Covid | 0.066*** | 0.038*** | 0.034*** | | | |
| | (0.011) | (0.010) | (0.010) | | | |
| Time Trend | -0.007*** | -0.003* | 0.005** | | | |
| | (0.002) | (0.002) | (0.002) | | | |
| WFH Exposure × Post Covid | | | | -0.022 | -0.024 | -0.016 |
| | | | | (0.076) | (0.074) | (0.081) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Company State × Industry FE | | ✓ | ✓ | | | |
| VC FE | | | ✓ | ✓ | ✓ | ✓ |
| Year FE | | | | ✓ | | |
| VC State × Year FE | | | | | ✓ | ✓ |
| Company State × Industry × Year FE | | | | | | ✓ |
| Observations | 46,321 | 46,286 | 45,087 | 43,879 | 44,147 | 43,760 |
| R-squared | 0.014 | 0.329 | 0.500 | 0.222 | 0.233 | 0.529 |

TABLE 2.24: **Company characteristics: Pre-VC Financing.** The table reports the results from OLS regressions following equation 2.1 in columns (1) to (3), and 2.2 in columns (4) to (6). The dependent variable is a dummy for having a financing round (from accelerators, angels, crowdfunding, etc.) before receiving the first VC financing. The regression dataset includes the first investment round received by a company between March, 2013, and July, 2022 and defined as "seed", or "early round". The unit of observation is the portfolio company-VC investor pair. Controls include a natural logarithm of the round's equity investment and the number of investors participating in the round in all specifications, a measure for the local venture capital availability defined as the natural logarithm of the total capital raised by VC funds in the VC's state lagged by one year in specifications without VC State × Year fixed effects, and company age and the natural logarithm of the total number of accelerators/angels/crowdfunding deals two years before the investment year. Standard errors are clustered at the VC investor level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

| | P(Had Pre-VC Financing) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Post Covid | 0.013 | 0.012 | 0.006 | | | |
| | (0.010) | (0.010) | (0.010) | | | |
| Time Trend | -0.011*** | -0.013*** | -0.011*** | | | |
| | (0.003) | (0.003) | (0.003) | | | |
| WFH Exposure × Post Covid | | | | -0.041 | -0.027 | 0.031 |
| | | | | (0.057) | (0.057) | (0.060) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Company State × Industry FE | | ✓ | ✓ | | | |
| VC FE | | | ✓ | ✓ | ✓ | ✓ |
| Year FE | | | | ✓ | | |
| VC State × Year FE | | | | | ✓ | ✓ |
| Company State × Industry × Year FE | | | | | | ✓ |
| Observations | 45,731 | 45,696 | 44,501 | 43,310 | 43,572 | 43,187 |
| R-squared | 0.104 | 0.131 | 0.249 | 0.226 | 0.236 | 0.319 |

TABLE 2.25: **Post-Covid Round Sizes.** The table reports the results from OLS regressions following equation 2.1 in columns (1) to (3), and 2.2 in columns (4) to (6). The dependent variable is the natural logarithm of the first-round equity financing received by the startup (deflated by the CPI). The regression dataset includes the first investment round received by a company between March, 2013, and July, 2022 and defined as "seed" or "early round". The unit of observation is the portfolio company - VC investor pair. Controls include a natural logarithm of the round's equity investment and the number of investors participating in the round in all specifications, and the natural logarithm of the total capital raised by VC funds in the VC's state lagged by one year in specifications without VC State × Year fixed effects. Standard errors are clustered at the VC investor level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

| | Ln(Round Size) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Post Covid | -0.030 | -0.014 | -0.017 | | | |
| | (0.026) | (0.024) | (0.022) | | | |
| Time Trend | 0.086*** | 0.085*** | 0.095*** | | | |
| | (0.006) | (0.005) | (0.005) | | | |
| WFH Exposure × Post Covid | | | | -0.225 | -0.143 | -0.011 |
| | | | | (0.168) | (0.155) | (0.159) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Company State × Industry FE | | ✓ | ✓ | | | |
| VC FE | | | ✓ | ✓ | ✓ | ✓ |
| Year FE | | | | ✓ | | |
| VC State × Year FE | | | | | ✓ | ✓ |
| Company State × Industry × Year FE | | | | | | ✓ |
| Observations | 45,731 | 45,696 | 44,501 | 43,310 | 43,572 | 43,187 |
| R-squared | 0.254 | 0.320 | 0.519 | 0.501 | 0.508 | 0.550 |

## 2.10 Appendix: Additional results

In this section, we investigate whether the increase in distance is observable for all types of deals or whether there is heterogeneity. We expect that in each industry, the distance will grow less for relatively larger deals due to the higher stakes involved. Investors are more likely to require substantial soft information and to anticipate a stronger need for future on-site monitoring when they risk large capital investments, and therefore they would, on average, locate closer to such deals. Table 2.26 reports the results of our event-study specification where we additionally interact the *Post Covid* dummy with a *Large Deal* variable. We characterize a deal as *Large* following the top 50th (columns (1)-(2)), 25th (columns (3)-(4)), and 10th (columns (5)-(6)) percentiles of deals ranked by size in the company's industry sector as defined by Pitchbook and in the same investment year. The results support that the post-Covid increase in distance is mainly driven by smaller deals. As we narrow the definition of a *Large Deal*, the coefficients of the interacted variables become more negative and remain strongly statistically significant. At the same time, the coefficient of *Post Covid* alone is always positive and statistically significant at a 1% level.

We then focus on some specific VCs to analyze from where this increase in distance is coming. Table 2.27 illustrates the change in the geographical distribution of investments for two VC firms - *Sequoia Capital* and a relatively smaller *Upfront Ventures*, both located in California. The table shows that the increase in distance for both VCs primarily comes from the decrease in the share of their investments located in California: for Sequoia, the share of new investments located in California decreased from 73% to 63% of total investments; for Upfront, from 83% to 58%. Instead, both firms invested relatively more in the states located on the East Coast (e.g., Massachusetts, Pennsylvania, etc.). Additionally, in our data, we observe that the average distance between the analyzed VCs and their portfolio companies located outside California also grew in the post-Covid period: on average, Sequoia's non-California companies are located 5% farther away (average distance was 3,381 km before Covid and is 3,546 km after Covid), while Upfront's - more than twice farther away (1,602 km vs. 3,279 km, respectively). Therefore, for these VCs, the distance increases both because they choose locations outside their home state more often and because when investing outside the home state they invest in farther locations, compared to before Covid.

TABLE 2.26: **Post-Covid Distance to Investments Depending on Deal Size.** The table reports the results of an OLS regression where the dependent variable is the natural logarithm of one plus the distance between the VC investor and the startup that received financing. The regression dataset includes the first investment round received by a company between March, 2013, and July, 2022, and defined as "seed" or "early stage". The unit of observation is the portfolio company-lead VC pair. In all specifications, controls include the number of investors participating in the round and the natural logarithm of the total capital raised by VC funds in the VC's state lagged by one year. *Large Deal* (Top 50p)/(Top 25p)/(Top 10p) is a dummy variable equal to one if the deal is above the median size/top 25th percentile/top 10th percentile of deals ranked by size in the company's industry sector in a specific investment year. Standard errors are clustered at the VC investor level. *** p<0.01, ** p<0.05, * p<0.1.

| | Ln(Distance+1) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Post Covid | 0.318*** | 0.307*** | 0.317*** | 0.252*** | 0.273*** | 0.205*** |
| | (0.094) | (0.085) | (0.082) | (0.074) | (0.077) | (0.070) |
| Post Covid x Large Deal (Top 50p) | -0.188** | -0.270*** | | | | |
| | (0.092) | (0.088) | | | | |
| Post Covid x Large Deal (Top 25p) | | | -0.367*** | -0.325*** | | |
| | | | (0.102) | (0.097) | | |
| Post Covid x Large Deal (Top 10p) | | | | | -0.477*** | -0.374*** |
| | | | | | (0.151) | (0.143) |
| Time Trend | 0.074*** | 0.055*** | 0.073*** | 0.055*** | 0.074*** | 0.055*** |
| | (0.014) | (0.013) | (0.014) | (0.013) | (0.014) | (0.013) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Company State × Industry FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| VC FE | | ✓ | | ✓ | | ✓ |
| Observations | 19,623 | 18,416 | 19,623 | 18,416 | 19,623 | 18,416 |
| R-squared | 0.084 | 0.364 | 0.085 | 0.364 | 0.084 | 0.364 |

TABLE 2.27: **Distance Increase - Case of Sequoia Capital and Upfront Ventures.** The table reports investments by two VC firms in pre- and post-Covid periods by the state of the portfolio companies' HQs. The data covers the period between October, 2017, and July, 2022, to ensure that periods before and after Covid are equal in length (conclusions remain the same if we use the data since March, 2013). The table shows the number of deals in each state (columns (1) and (3)), the share of deals in the state relative to the total number of deals in the period (columns (2) and (4)), and the change in the deals share in the state between the analyzed periods (column (5)).

**Panel A: Sequoia Capital**

| | Before Covid | | After Covid | | |
|---|---|---|---|---|---|
| Company's HQ State | N deals | Deals Share | N deals | Deals Share | Δ Share |
| | (1) | (2) | (3) | (4) | (5) |
| California | 36 | 73% | 40 | 63% | -10% |
| Colorado | 1 | 2% | - | 0% | -2% |
| Connecticut | 1 | 2% | - | 0% | -2% |
| Delaware | - | 0% | 2 | 3% | 3% |
| Florida | 1 | 2% | 1 | 2% | 0% |
| Illinois | - | 0% | 1 | 2% | 2% |
| Indiana | - | 0% | 1 | 2% | 2% |
| Massachusetts | - | 0% | 3 | 5% | 5% |
| New Hampshire | - | 0% | 1 | 2% | 2% |
| New York | 6 | 12% | 7 | 11% | -1% |
| North Carolina | 1 | 2% | - | 0% | -2% |
| Pennsylvania | - | 0% | 2 | 3% | 3% |
| Tennessee | 1 | 2% | 1 | 2% | 0% |
| Texas | - | 0% | 1 | 2% | 2% |
| Washington | 2 | 4% | 3 | 5% | 1% |
| Total | 49 | 100% | 63 | 100% | |

**Panel B: Upfront Ventures**

| | Before Covid | | After Covid | | |
|---|---|---|---|---|---|
| Company's HQ State | N deals | Deals Share | N deals | Deals Share | Δ Share |
| | (1) | (2) | (3) | (4) | (5) |
| Arizona | 1 | 4% | - | 0% | -4% |
| California | 20 | 83% | 11 | 58% | -25% |
| Florida | - | 0% | 1 | 5% | 5% |
| Georgia | - | 0% | 1 | 5% | 5% |
| Indiana | 1 | 4% | - | 0% | -4% |
| Massachusetts | - | 0% | 1 | 5% | 5% |
| New York | - | 0% | 2 | 11% | 11% |
| North Carolina | - | 0% | 1 | 5% | 5% |
| Oregon | 1 | 4% | - | 0% | -4% |
| Texas | - | 0% | 1 | 5% | 5% |
| Washington | 1 | 4% | 1 | 5% | 1% |
| Total | 24 | 100% | 19 | 100% | |

## 2.11 Appendix: Performance insights

The question of whether online deal sourcing delivers better or worse performance results than the traditional one is important enough to have a preliminary analysis, even though the post-Covid time series only allows to have early insights into this thus far. As we have 29 months of data since the beginning of the pandemic, which is a period shorter than the average time needed for exits, we primarily focus on the probability of raising the second VC round as the most reliable intermediate outcome measure.[25] We analyze the probability of getting the second round within 12 and 18 months since the first VC financing.[26] We provide the results of examining the likelihood of startup exits via IPO or M&A within 18 months since the first VC financing in Table 2.29. We use the same regression specifications as in equations 2.1 and 2.2, where the dependent variable is a dummy for whether the company received a second round or not/exited or not. To ensure that specific market conditions do not drive the exit results, we include a range of additional controls (for IPO, M&A, VC activities) in our regressions.

Table 2.28 reports results on the probability of receiving a second VC financing round within 12 months and 18 months after receiving the first round. First, we concentrate on the regression results based on equation 2.1, where the coefficient on the *Post Covid* dummy shows how much the probability of receiving a second round of financing changed after Covid-19. When focusing on a period of 12 months, we observe, in columns (1) to (3), that the likelihood of getting a second round is higher for companies that received their first VC financing during the post-Covid period compared to those funded before. Columns (7) to (9) suggest a similar conclusion for the probability of receiving a second round within 18 months. The coefficients' magnitude implies that companies that obtained their first round after Covid, respectively, are around 11 (for 12-month period) and 13 (for 18-month period) percentage points more likely to receive a follow-up round of financing, which is a significant increase in the probability.[27] In general, results suggest that at least in the first months since the beginning of the pandemic, VCs are

[25] Hochberg, Ljungqvist, and Lu, 2007 highlights that one-third of the companies in their sample do not survive the first round of financing and are thus written off.

[26] When considering the probability of getting a second round within a year (18 months), we need to drop companies that obtained financing in less than the last 12 (18) months of our main sample because we are not able to observe in the data whether a second round will exist within a year (18 months) or not.

[27] However, we lose many observations because of the data truncation in the latter specifications.

following up with further rounds of financing to companies sourced online not less than to those companies they decided to finance before the pandemic.

Next, we use the regression model in equation 2.2, where a measure of VC exposure to high remote-work industries is interacted with *Post Covid* dummy variable. As VCs that had exposure to more remote-work industries may be more familiar with or capable of acquiring information through online communications about startups or their founders, they may invest in startups with higher probability of survival and getting a second round of financing. However, columns (4) to (6) and (10) to (12) show that VCs with higher exposures to remote-work industries do not invest in startups that are more likely to get a second round of financing. These regressions do not undermine the observation that, in general, the probability of getting a second round of financing did not decrease for investments made after Covid-19.

Table 2.29 investigates whether the probability of going public or being acquired changes after the onset of Covid-19. It shows that the probability of exit for companies that received the first round of financing post-Covid is slightly higher than for those that received it before the pandemic. The table also reveals that deals financed by VCs with more exposure to remote-work industries do not experience a higher probability of exit through an IPO or an M&A. Thus, these findings provide suggestive evidence that startups financed after the Covid-19 pandemic perform similarly or even better in terms of fast exits compared to those funded before Covid.

TABLE 2.28: **Probability to receive a second round of financing.** The table reports the results from OLS regressions following equation 2.1 in columns (1) to (3) and (7) to (9), and 2.2 in columns (4) to (6) and (10) to (12). The dependent variable is a dummy for whether the startup received a second round of financing within 12 months (columns (1) to (6)) and within 18 months (columns (7) to (12)) since its first VC financing. The regression dataset includes companies that obtained their first VC financing round defined as "seed" or "early round" between March, 2013, and July, 2021 (for 12-month period analysis) and between March, 2013, and January, 2021 (for 18-month period analysis): columns (1) to (6) do not include companies that received their first financing from August 2021 onward, and columns (7) to (12) do not include companies with first financing from February 2021 to drop companies for which we cannot observe full 12 or 18 months after their first VC investment, respectively. The unit of observation is the portfolio company-VC investor pair. Controls include company age, a natural logarithm of the first round's equity investment, the number of investors participating in the first VC round, and a measure for the local venture capital availability defined as the natural logarithm of the total VC capital raised in the state of the lead VC investor lagged by one year in specifications without VC State × Year fixed effects. Standard errors are clustered at the lead VC investor level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

| | P(Second Round) | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Within 12 Months | | | | | | Within 18 Months | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| Post Covid | 0.115*** | 0.115*** | 0.110*** | | | | 0.130*** | 0.132*** | 0.124*** | | | |
| | (0.007) | (0.007) | (0.007) | | | | (0.009) | (0.009) | (0.010) | | | |
| Time Trend | -0.010*** | -0.010*** | -0.009*** | | | | -0.008*** | -0.009*** | -0.007*** | | | |
| | (0.001) | (0.001) | (0.001) | | | | (0.001) | (0.001) | (0.002) | | | |
| WFH Exposure × Post Covid | | | | 0.026 | 0.017 | 0.026 | | | | -0.035 | -0.061 | -0.071 |
| | | | | (0.061) | (0.063) | (0.068) | | | | (0.089) | (0.092) | (0.097) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Company State × Industry FE | | ✓ | ✓ | | | | | ✓ | ✓ | | | |
| VC FE | | | ✓ | ✓ | ✓ | ✓ | | | ✓ | ✓ | ✓ | ✓ |
| Year FE | | | | ✓ | | | | | | ✓ | | |
| VC State × Year FE | | | | | ✓ | ✓ | | | | | ✓ | ✓ |
| Company State × Industry × Year FE | | | | | | ✓ | | | | | | ✓ |
| Observations | 40,201 | 40,163 | 39,009 | 38,521 | 38,754 | 38,405 | 36,793 | 36,755 | 35,618 | 35,451 | 35,661 | 35,337 |
| R-squared | 0.022 | 0.040 | 0.114 | 0.094 | 0.104 | 0.185 | 0.032 | 0.049 | 0.133 | 0.116 | 0.125 | 0.199 |

TABLE 2.29: **Probability of Exit through IPO or M&A.** The table reports the results from OLS regressions following equation 2.1 in columns (1) to (3) and (7) to (9), and 2.2 in columns (4) to (6) and (10) to (12).The dependent variable is a dummy for whether the startup went public or was acquired (columns (1) to (6)) within 18 months, and whether it exited via M&A (versus staying private, columns (7) to (12)) separately. The regression dataset includes companies that obtained their first VC financing round defined as "seed" or "early round" between March, 2013, and January, 2021: the dataset does not include companies that received their first financing from February 2021 (to drop companies for which we cannot observe full 18 months after their first VC investment). The unit of observation is the portfolio company-VC investor pair. Controls include company age, a natural logarithm of the first round's equity investment, the number of investors participating in the first VC round, a measure for the local venture capital availability defined as the natural logarithm of the total VC capital raised in the state of the lead VC investor lagged by one year in specifications without VC State × Year fixed effects, the median of the yearly book-to-market ratio of all public companies in the same industry, and a lagged measure of the number of IPOs and M&As for columns (1) to (6), and of M&A in columns (7) to (12). Standard errors are clustered at the lead VC investor level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

| | Probability of Exit Within 18 Months | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | P(IPO or M&A) | | | | | | P(M&A) | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| Post Covid | 0.017*** | 0.017*** | 0.018*** | | | | 0.027*** | 0.026*** | 0.029*** | | | |
| | (0.004) | (0.004) | (0.004) | | | | (0.003) | (0.003) | (0.004) | | | |
| Time Trend | -0.008*** | -0.009*** | -0.009*** | | | | 0.006*** | 0.006*** | 0.006*** | | | |
| | (0.001) | (0.001) | (0.001) | | | | (0.001) | (0.001) | (0.001) | | | |
| WFH Exposure x Post Covid | | | | -0.010 | -0.002 | 0.009 | | | | 0.027 | 0.030 | 0.023 |
| | | | | (0.037) | (0.038) | (0.036) | | | | (0.027) | (0.028) | (0.028) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Company State x Industry FE | | ✓ | ✓ | | | | | ✓ | ✓ | | | |
| VC FE | | | ✓ | ✓ | ✓ | ✓ | | | ✓ | ✓ | ✓ | ✓ |
| Year FE | | | | ✓ | | | | | | ✓ | | |
| VC State x Year FE | | | | | ✓ | ✓ | | | | | ✓ | ✓ |
| Company State x Industry x Year FE | | | | | | ✓ | | | | | | ✓ |
| Observations | 36,231 | 36,198 | 35,066 | 34,942 | 35,144 | 34,827 | 36,060 | 36,027 | 34,896 | 34,773 | 34,974 | 34,656 |
| R-squared | 0.011 | 0.027 | 0.106 | 0.098 | 0.107 | 0.168 | 0.022 | 0.037 | 0.104 | 0.127 | 0.136 | 0.196 |

# References

Agarwal, Sumit and Robert Hauswald (2010). "Distance and Private Information in Lending". In: *The Review of Financial Studies* 23.7, pp. 2757–2788.

Bellucci, Andrea et al. (2023). "The reallocation effects of COVID-19: Evidence from venture capital investments around the world". In: *Journal of Banking & Finance* 147, p. 106443.

Bengtsson, Ola and S. Abraham Ravid (2009). "The geography of venture capital contracts". In: *Working Paper*.

Berger, Allen N. et al. (2005). "Does function follow organizational form? Evidence from the lending practices of large and small banks". In: *Journal of Financial Economics* 76.2, pp. 237–269. ISSN: 0304-405X.

Bernstein, Shai, Xavier Giroud, and Richard R. Townsend (2016). "The impact of venture capital monitoring". In: *The Journal of Finance* 71.4, pp. 1591–1622.

Brander, James A., Raphael Amit, and Werner Antweiler (2002). "Venture-Capital Syndication: Improved Venture Selection vs. The Value-Added Hypothesis". In: *Journal of Economics & Management Strategy* 11.3, pp. 423–452.

Buffington, Catherine et al. (2020). "Measuring the effect of COVID-19 on U.S. small businesses: The small business pulse survey". In.

Bygrave, William D. (1987). "Syndicated investments by venture capital firms: A networking perspective". In: *Journal of Business Venturing* 2.2, pp. 139–154.

Callaway, Brantly, Andrew Goodman-Bacon, and Pedro HC Sant'Anna (2024). *Difference-in-differences with a continuous treatment*. Tech. rep. National Bureau of Economic Research.

Casamatta, Catherine and Carole Haritchabalet (2007). "Experience, screening and syndication in venture capital investments". In: *Journal of Financial Intermediation* 16.3, pp. 368–398. ISSN: 1042-9573.

Chen, Henry et al. (2010). "Buy local? The geography of venture capital". In: *Journal of Urban Economics* 67.1, pp. 90–102.

Chen, Jun and Michael Ewens (2021). *Venture Capital and Startup Agglomeration*. Tech. rep. National Bureau of Economic Research.

Cumming, Douglas and Na Dai (2010). "Local bias in venture capital investments". In: *Journal of Empirical Finance* 17.3, pp. 362–380. ISSN: 0927-5398.

Dingel, Jonathan I. and Brent Neiman (2020). "How many jobs can be done at home?" In: *Journal of Public Economics* 189, p. 104235. ISSN: 0047-2727.

Fairlie, Robert (2020). "The impact of COVID-19 on small business owners: Evidence from the first 3 months after widespread social-distancing restrictions". In: *Journal of Economics & Management Strategy* 29.4, pp. 727–740.

Fazio, Catherine E et al. (May 2021). "How is COVID Changing the Geography of Entrepreneurship? Evidence from the Startup Cartography Project". In: *NBER Working Papers* 28787.

Giroud, Xavier (2013). "Proximity and investment: Evidence from plant-level data". In: *The Quarterly Journal of Economics* 128.2, pp. 861–915.

Gompers, Paul, Will Gornall, Steven K. Kaplan, et al. (2020). "How do venture capitalists make decisions?" In: *Journal of Financial Economics* 135.1, pp. 169–190.

Gompers, Paul, Will Gornall, Steven N. Kaplan, et al. (2021). "Venture Capitalists and COVID-19". In: *Journal of Financial and Quantitative Analysis* 56.7, pp. 2474–2499.

Gompers, Paul, Anna Kovner, and Josh Lerner (2009). "Specialization and Success: Evidence from Venture Capital". In: *Journal of Economics & Management Strategy* 18.3, pp. 817–844.

Gompers, Paul and Josh Lerner (2000). "Money chasing deals? The impact of fund inflows on private equity valuation". In: *Journal of Financial Economics* 55.2, pp. 281–325. ISSN: 0304-405X.

Hale, Thomas et al. (2021). "A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker)". In: *Nature Human Behaviour* 5.4, pp. 529–538.

Han, Pengfei et al. (2022). "Invest local or remote? The effects of COVID-19 lockdowns on venture capital investment around the world". In: *Working Paper*.

Hochberg, Yael V., Laura A. Lindsey, and Mark M. Westerfield (2015). "Resource accumulation through economic ties: Evidence from venture capital". In: *Journal of Financial Economics* 118.2, pp. 245–267.

Hochberg, Yael V., Alexander Ljungqvist, and Yang Lu (2007). "Whom You Know Matters: Venture Capital Networks and Investment Performance". In: *The Journal of Finance* 62.1, pp. 251–301.

— (2010). "Networking as a Barrier to Entry and the Competitive Supply of Venture Capital". In: *The Journal of Finance* 65.3, pp. 829–859.

Howell, Sabrina et al. (2020). "How resilient is venture-backed innovation? Evidence from four decades of U.S. patenting". In: *NBER Working Paper*.

Lerner, Joshua (1994). "The Syndication of Venture Capital Investments". In: *Financial Management* 23.3, pp. 16–27.

— (1995). "Venture Capitalists and the Oversight of Private Firms". In: *The Journal of Finance* 50.1, pp. 301–18.

Liberti, José María and Mitchell A Petersen (2018). "Information: Hard and Soft". In: *The Review of Corporate Finance Studies* 8.1, pp. 1–41.

Petersen, Mitchell A and Raghuram G Rajan (2002). "Does Distance Still Matter? The Information Revolution in Small Business Lending". In: *The Journal of Finance* 57.6, pp. 2533–2570.

Sorenson, Olav and Toby E Stuart (2001). "Syndication Networks and the Spatial Distribution of Venture Capital Investments". In: *American Journal of Sociology* 106.6, pp. 1546–1588.

— (2008). "Bringing the Contex Back in: Settings and the Search for Syndicate Partners in Venture Capital Investment Networks". In: *Administrative Science Quarterly* 53.2, pp. 266–294.

Srivastava, Jagriti and Balagopal Gopalakrishnan (2022). "Work from home amenability and venture capital financing during COVID-19". In: *Applied Economics* 54.44, pp. 5073–5098.

Stein, Jeremy C. (2002). “Information Production and Capital Allocation: Decentralized versus Hierarchical Firms”. In: *The Journal of Finance* 57.5, pp. 1891–1921.

Tian, Xuan (2011). “The Role of Venture Capital Syndication in Value Creation for Entrepreneurial Firms”. In: *Review of Finance* 16.1, pp. 245–283.

Zhang, Lei, Anil K. Gupta, and Benjamin L. Hallen (2017). “The Conditional Importance of Prior Ties: A Group-Level Analysis of Venture Capital Syndication”. In: *Academy of Management Journal* 60.4, pp. 1360–1386.

# 3 Innovating to Net Zero: Can Venture Capital and Startups Play a Meaningful Role?

*with Ramana Nanda*

## 3.1 Introduction

As the consequences of rising global temperatures and related climate change are becoming more apparent, a growing number of countries – covering over 70% of global $CO_2$ emissions – have committed in recent years to work towards achieving Net-Zero emissions by 2050, in an effort to limit long-term increase in global temperatures to 1.5° C. Despite this progress, a seminal report released by the International Energy Agency ("Net Zero by 2050 - A Roadmap for the Global Energy Sector" 2022) notes that about half the projected $CO_2$ reductions that will be required to achieve Net Zero by 2050 will depend on technologies that are currently not commercially viable– highlighting the critical need for breakthrough innovations to mitigate the impacts of climate change.

In this chapter, we discuss the prevalence and focus of U.S. innovation related to achieving Net-Zero targets, with a particular focus on the potential role played by Venture Capital-backed startups. We identify patents related to the mitigation of climate change using tags developed by the the Cooperative Patent Classification (CPC).[1] The classification scheme was put together with the help of experts in the field, including the Intergovernmental Panel on Climate Change (IPCC), and was developed to tag technologies with certain attributes rather than to replace the classification of technologies themselves. As described in Table 3.1, the Y02 subclasses include areas related to specific clean energy technologies, but also technologies related

[1]The Cooperative Patent Classification is a patent classification system, which has been jointly developed by the European Patent Office and the United States Patent and Trademark Office.

to energy efficiency, transportation, industrial production and carbon capture and sequestration –that have the potential to mitigate climate change through lowering green house gas in the atmosphere. Together, these technologies account for about 6.5% of all utility patents in the USPTO between 2000 and 2020, but have grown at over twice the rate of other patents in the USPTO since 2010.

The IEA report ("Net Zero by 2050 - A Roadmap for the Global Energy Sector" 2022) notes that breakthrough innovations are likely to be particularly important in areas such as energy generation & storage, industrial production and in carbon capture & sequestration, given their current contribution to $CO_2$ emissions relative to what is required by 2050. Using a measure of a patent's reliance on fundamental science developed by Marx and Fuegi, 2020, we show that patents in these sectors tend to cite fundamental science much more intensively than other sectors such as energy efficiency, ICT and transportation. We refer to these three more science-intensive sectors as the subset of Net-Zero patents that are 'deep tech'.

The fact that these deep tech sectors coincide with the areas that require the biggest breakthrough innovations is important in light of growing evidence that large corporations have pulled back considerably from fundamental innovation in recent years (Arora, Belenzon, and Patacconi, 2018; Arora, Belenzon, Patacconi, and Suh, 2020). Moreover, a large body of academic research has highlighted how the organizational form associated with the commercialization of innovations can have first order effects on the degree to which radical versus incremental innovations are brought to market (Akcigit and Kerr, 2018). The bureaucratic organizational structure and related incentives in large firms are often not conducive to radical innovations (Kortum and Lerner, 2000). Moreover, large corporations often have weaker incentives to commercialize technologies that compete with core lines of business (Reinganum, 1983; Cunningham, Ederer, and Ma, 2021). This suggests an important role for 'deep tech' inventions emerging from universities and the related importance of sources of finance such as Venture Capital to help support their commercialization.

Consistent with this view, we find that patents associated with mature firms have the lowest citations to science, while VC-backed startups, which tend to be the most science-intensive on average, have over three-times the number of scientific citations compared to mature firms. In addition, when examining the influence of patents, we find that Net Zero patents granted to

VC backed startups are three to six times more likely to be in the top percentile of patents in terms of citations received, when compared to USPTO patents granted to mature firms in a same technology class and granted in the same year. This higher influence of VC-backed patents compared to mature firms within Net Zero patents is even larger than the differential identified by S. Howell et al., 2020 in their analysis of VC-backed patenting in general.

Despite the greater influence and scientific reliance of VC-backed patents which are likely to be of particular relevance in deep tech sectors, we nevertheless also note that VC-backed patents comprise under 3% of all Net-Zero patents and moreover, have disproportionately grown in non-deep tech areas such as energy efficiency and transportation in recent years. In Sections 3 and 4, we discuss potential frictions and possible solutions related to the commercialization of climate-related deep tech that might enable venture capital-backed startups to play a more meaningful role in supporting the transition to Net-Zero in the coming decades.

## 3.2 Innovations related to Net-Zero

### 3.2.1 Identifying Net-Zero Patents

We focus on patents granted by the USPTO from 2000 and 2020, restricting the analysis to utility patents.[2] To identify innovations related to Net-Zero, we use a novel classification scheme that is part of the Cooperative Patent Classification (CPC) System. The CPC classification is the result of a partnership between the European Patent Office (EPO) and the USPTO that was implemented in 2013. The aim of this project was to harmonize the different classification systems in place, and to bring the best practices from both Offices together [3]. The Y02 category that identifies environmental technologies was first introduced in January 2013 [4]. More sub-classes of that same category were then added in 2015 and 2018, and the scheme is now considered

[2] We obtain patent data from PatentsView.org, a platform that provides data from the United States Patent and Trademark Office (USPTO). We only keep patents for which we observe information on: the date it was applied for, the date it was granted, the patent title, the organization it was assigned to, the type of organization and its CPC technology classification. With these restrictions, our sample comprises 90.3% of the 5,367,164 patents granted over this period.

[3] https://www.cooperativepatentclassification.org/about

[4] https://www.uspto.gov/about-us/news-updates/uspto-and-epo-announce-launch-cooperative-patent-classification-system

to be complete, with 8 main categories, that are reported in Table 3.1.[5]

The aim of this categorization is to extend the reach of patents related to 'green' technologies to a wider range of stakeholders, including non experts. As such, the Y02 categorization works as a separate class applied by the patent office, that is considered additional to standard classifications of technology classes. An important feature of this categorization is that it spans many different fields and it is able to capture innovations in both mitigation and adaptation technologies (Haščič and Migotto, 2015). This allows for a compelling way to classify ICT and related energy efficiency technologies that are typically harder to classify in terms of their contribution to climate change mitigation.[6]

As shown in Table 3.1, the classification system of climate change technologies include innovations related both to climate change mitigation and to adaptation. A deeper examination of the adaptation technologies tagged in Y02A shows that they are largely related to technologies helping to address growing threats of vector-borne, fly-borne, or waterborne diseases whose impact is exacerbated by climate change. Y02W is focused on waste management and wastewater. While technologies in these two groups can play a role in climate change, they are less related to addressing the specific goals related to reaching Net Zero targets, so we exclude them from our analysis.

For our analysis we therefore focus on the six main categories related to Net-Zero. Panel A of Figure 3.1 reports the number of Net-Zero patents

[5]Cohen, Sauermann, and P. Stephan, 2020 use the same classification system to examine patenting differences between mature publicly-traded firms to the link between the ESG-ratings of these firms and their innovation. Our analysis focuses on the universe of firms regardless of whether they are publicly traded.

[6]In the CPC tagging, a patent can belong to multiple Y02 classes. However, this happens for a minority of patents. 293,278 out of 356,996 (82.2%) belong to one group only. In the case of patents being assigned to more than one Y02 class, we proceed to allocate each patent to a unique group as follows: first, we sum the number of subcategories for each group. We allocate the patent to the group that has the highest number of sub-classes with the rationale that a patent with more tags in one group suggests that this group is the most relevant for the patent. This procedure is applied to 20,191 patents (6% of total). Second, for patents that do not have a prevalent sub-class, we allocate them to one group after considering the different combinations of sub-classes. When carbon captures technologies are combined with energy efficiency classes, this is usually because GHG obtained with carbon capture can be also used for other purposes. In this case we consider carbon capture as the main technology group. When technologies related to transportation, efficiency in buildings and ICT are combined with classes such as energy generation, this is because they are related to technologies that improve energy efficiency, and make use of energy from renewable sources, in this case we keep the main intended use of the technology (home appliances, car engines and batteries, etc.) as the main technology group. Lastly, when the sub-class of energy generation is combined with waste, it is because these are technologies related to fuels obtained from waste, so we consider them as generation technologies. Overall this second step is applied to 41,694 of patents, which represents 11.7% of total.

granted by the USPTO from 2000 to 2020 in relation to all other USPTO patents, where Net-Zero patents refer to the six categories of Y02 patents noted above that are related to achieving Net-Zero targets. As can be seen from Panel A, Net-Zero patents constitute a small share of total patents in the USPTO, but have grown from 4% in 2000 to 8% in 2020.

Panel B reports the growth of Net Zero patents and all other patents relative to the baseline year 2000. As can be seen from Panel B, Net-Zero patents have grown over twice as fast as other patents in the USPTO, with a large inflection emerging in 2010. The inflection seen in 2010 could represent changing fundamentals driving an increase in Net-Zero innovation, or could be driven at least in part by the new classification being implemented in those years leading to a greater focus on these technologies.[7]

We turn next to validating the CPC classification using text taken from the titles of all Net Zero patents and identifying distinctive words associated with patents in each category. The distinct words associated with each category are derived using a Term Frequency - Inverse Document Frequency (TF-IDF) procedure, where the frequency of each word in a document (TF) is weighted by the inverse of the frequency across all documents in the corpus (IDF).[8] Panels A to F of Figure 3.2 report word clouds of the content of patents titles of the six Net-Zero categories. As can be seen from Figure 3.2, the types of keywords emerging from the patent titles in each of these categories appear intuitive, which is reassuring in terms of the quality of the classification. Figure 3.3 shows the total trend of patents in each of these categories from 2000 to 2020. In relative terms the highest growth was reported in the category of mitigation technologies related to household appliances and ICT. Column 1 of Table 3.2 reports the precise number of Net Zero patents issued in each category over the 2000 to 2020 period, ranging from just over 4,000 patents for GHG capture to nearly 110,000 patents related to generation and storage.

[7] Although the classification was applied retrospectively, it is possible that it was more effective for identifying patents applied for from that moment on.

[8] In our dataset, each list of patents titles belonging to a certain category is a separate document, and the corpus is composed by all documents. We start by cleaning the text of titles and removing all punctuation and special characters, and use lemmatization to group together the inflected forms of a word in order to be analysed as a single term. We then apply a list of stop-words to be excluded from the frequency count. The list includes standard English stop-words, as well as USPTO stop-word lists that are specific for technical language processing. With TF-IDF we then add a list of stop-words created from terms that are recurrent in all documents of the corpus. The frequency of the remaining words is then adjusted for how rarely a word is used in the corpus.

### 3.2.2 'Deep Tech' Sectors that rely more on fundamental science

As noted in the introduction, one of our goals is to understand differences in the Net-Zero sectors in terms of their reliance on fundamental science as this is likely to impact the commercialization frictions they face. The word clouds reported in Figure 3.2 provide an intuitive sense that the first three categories of renewable energy generation & storage, carbon capture & sequestration and industrial production are likely to be much more reliant on fundamental science relative to the the categories related to energy efficiency and transportation. However, we also validate this intuition using data provided by Marx and Fuegi, 2021, that identifies citations that a patent makes to scientific papers.[9]

Column 2 of Table 3.2 reports the share of patents in each category that cites at least one scientific paper. As can be seen from the Table, the first three rows correspond to sectors with a much greater reliance on science. Between a third and half of all patents cite science in these sectors, compared to 27% for all utility patents over the 2000-2020 period. Columns 3-8 report the means and quantiles of scientific paper citations of these patents, conditional on citing at least one science paper. They reinforce the stark difference in reliance on science across these categories. Not only do the first three sectors have a much greater propensity to cite science at the extensive margin, but have a significantly greater intensity of reliance on science, as can be seen by the larger number of scientific papers cited at all points above the 25th percentile. As noted before, these deep tech categories coincide with the sectors where we need some of the most important breakthrough innovations to reach Net Zero targets. We return to this fact and the implications for policy in the subsequent sections.

### 3.2.3 The Role of Venture Capital

We turn next to understand differences in Net Zero patenting by the type of assignee. To do so, we first distinguish firms from other assignees such as universities, government labs and individuals by supplementing the USPTO classification of assignees (as reported in the disambiguated assignee data)

[9] The authors link data from the USPTO to a broad set of scientific articles not limited by industry or field. Their algorithm can capture up to 93% of patent citations to science with an accuracy rate of 99% or higher.

with text analysis to better distinguish institutions, hospitals and universities from the company or corporation group.[10]

Within firms, we further distinguish between mature firms, young firms and those backed by venture capital. We define young firms as those whose first patent was granted less than 10 years before the focal patent. In other words the same firm could have some of its patents categorized as being associated with a young firm indicator and others being associated with mature firm indicator. Finally, we merge the patent data with the Refinitiv VentureXpert database, following a similar procedure to Bernstein, Giroud, and Townsend, 2016 in order to identify venture capital-backed startups.[11]

In light of the fact that corporations have been documented to be pulling back from fundamental research in recent years (Arora, Belenzon, and Patacconi, 2018; Arora, Belenzon, Patacconi, and Suh, 2020), we turn next to looking specifically at firm-type differences in Net Zero patents, given the particular importance of deep tech innovations in order to achieve Net Zero targets. As seen in Table 3.3, mature companies account for about two-thirds of the Net Zero patents granted between 2000 and 2020. A further fifth is accounted for by 'young' firms. VC-backed firms account for just under 3% of Net Zero patents. Universities, government labs and individuals account for the balance. Columns 3-8 look at variation in the share of these patents by the different Net Zero sectors. Generation and Storage accounts for the largest relative share of patents for all assignees. However, it can be seen that while all the other assignees have 40-50% of their Net Zero patents in this category, mature companies have a relatively smaller 30% share in generation and storage. In comparison, mature companies have a much larger relative share of patents related to mitigation in Transport. Energy Efficiency

[10] This is performed taking into account that inventors are international, so the same word that indicates for example a university, has to be considered in different languages.

[11] We start by matching each standardized name of a company in VentureXpert with standardized names from the USPTO dataset: if an exact match is found, this is taken to be the same company and removed from the list. For the remaining companies, we use a fuzzy matching technique that gives a similarity score to matches of stem names weighted by the inverse frequency of use of each word in the names list. If a similarity score higher than 85% is found, we combine this information with other identifying information, such as founding dates and patents grant dates, and standardized city/nation combination. In the overall sample of international startups we identify 18,987 startups that have at least one patent granted by the USPTO, this is approximately 20% of the overall VentureXpert dataset of VC-backed startups and this ratio is in line with other papers matching these two datasets. As we want to identify innovations that are in the portfolios of VC and not all innovations belonging to companies that were funded by VCs many years beforehand, we apply two more restrictions: first, we define a patent to be VC-backed if it was applied for between the first and last round of financing by VC funds. Second, we restrict patent level that indicates if a patent is applied for within 10 years since the first patent was issued by that same firm.

in buildings and ICT account for between 30% and 35% of patents for all the firms. GHG capture has a very small share of patents across all assignees, with the greatest relative share coming from universities, government labs and individuals.

Looking at the sum of shares for Deep Tech patents (columns 3-5) vs. Non Deep Tech (columns 6-8) for different assignees in Table 3.3, it can be seen that Deep Tech constitutes a larger share of VC-backed firms' overall patenting (60%), compared to young firms (55%) and mature firms (44%). In Table 3.4, we document the degree to which patents granted to different assignees rely on fundamental science, broken down by whether or not the patent is in one of the three deep tech categories. The difference between the average number of scientific citations between Deep Tech and non Deep Tech for all assignee groups is consistent with the pattern documented in Table 3.2. However, it is also striking that VC-backed firms are much more likely to cite fundamental science relative to firms in general. This is driven by both the extensive and intensive margin, as well as the fact that (as seen in Table 3.3), VC-backed firms have a larger share of deep tech patents among the set of patents that they have been granted.

Another way of examining differences in nature of patenting by assignees is to look at the impact of these patents through their citations. In Table 3.5, we report the share of patents granted to each type of assignee that are in the top (10 and 1) percentiles in terms of citations received, relative to all other patents granted in the same year across the entire USPTO patent database. The reason for looking at the right tail of citations is that some patenting is 'defensive'. Looking at the most highly cited patents gives a better indication of the degree to which there is a pattern in terms of the firms where the most influential patents are being developed. Given the large share of patents comprised by these assignees, we see that Net-Zero patents filed by other – particularly mature – firms are about proportional to what might expect at random, albeit a bit less influential. These results are consistent with mature firms focusing more on incremental, sustaining innovations. On the other hand, and consistent with the findings of S. Howell et al., 2020, we find that VC-backed startups are disproportionately likely to have top cited patents. They are almost three times more likely than random to have Net Zero patents that are in the top 10% of citations and almost 5 times times more likely to have patents in the top 1% of citations. Given the role that Venture Capital can play in stimulating breakthrough innovation (Kortum and Lerner, 2000; Bernstein, Giroud, and Townsend, 2016; Lerner and Nanda, 2020), these results suggest that VC has the potential to play an increasingly important role in helping to drive the breakthrough innovations needed to achieve Net Zero targets.

Despite the outsized impact the VC-backed patents appear to have among Net Zero patenting, one potential limitation of Venture Capital's impact is the small number of firms and Net Zero patents it is associated with. However, this is equally true of VC-backed innovations in general and yet VC-backed firms are associated with some of the most innovative, transformational and valuable firms in the world (Lerner and Nanda, 2020). Of potentially greater concern is that fact that, following a brief increase during a boom in venture financing for renewable energy startups (Nanda, Younge, and Fleming, 2014; Popp et al., 2020), Venture Capital funding within Net Zero is increasingly associated with non-deep tech patents. Figure 3.4 shows that while venture capital-backed startups continue to dominate mature firms in terms of the share of deep tech patenting in Net Zero, the share has declined from over 70% in 2012 to about 55% in 2020.

## 3.3 Potential Frictions in Financing Deep Tech

Venture Capital investment in the US – encompassing all investments, not just those related to Net Zero – has grown substantially since the early 2000s. The number of startups doubled over this period and the amount of capital being invested has risen more than five-fold since the early 2000s. However, as Lerner and Nanda, 2020 note, this growth has not been uniform. It has come disproportionately from sectors such as IT software and related services such as consumer internet, enterprise software and media and communication. Hardware, Energy, materials, and resources combined accounted for about 10% of capital invested by VCs in 2020, falling from a high of 40% in earlier part of the sample. To some extent, these ebbs and flows of funding across sectors reflect technology life cycles, the huge wave of application-related innovations made possible by the Internet revolution in the late 1990s, and the subsequent rise of cloud computing in the mid-2000s (Nanda, Samila, and Sorenson, 2020). Nevertheless, growing academic research has begun to articulate certain aspects of start-ups that tend to make them have lower risk-adjusted returns and hence less attractive to Venture Capital investors. We turn next to reviewing this work.[12]

[12]This section draws extensively on Nanda, Younge, and Fleming, 2014, Nanda and Rhodes-Kropf, 2016 and Nanda, Samila, and Sorenson, 2020.

### 3.3.1 Capital Intensity and Time Scale of Experimentation Cycles

Venture Capital (VC) investors do not shy away from investing large sums of money, particularly when financing the *scale-up* of successful ventures. Many business-to-consumer social networks and business-to-business enterprise software firms have raised hundreds of millions, or even billions, of dollars of equity financing from Venture Capital investors in the prior decade.

However, VCs are particularly sensitive to how much time and money it takes to achieve *initial* de-risking milestones. To see why, it is useful to recognize the skewed nature of risk and return in VC: over half of the investments that even the most successful VCs make fail entirely, while the majority of return for VC firms is generated by one or two extremely successful investments that are very hard to predict (Kerr, Nanda, and Rhodes-Kropf, 2014). VCs therefore invest in stages, where each stage or round of financing by the VC can be thought of as an experiment that generates information about whether or not a start-up can achieve its promised potential. Staged financing is tied to milestones and effectively gives VCs real options—they can choose to invest further in the next round of financing when start-ups achieve milestones, or they can choose to abandon follow-on financing if they do not feel the start-up is showing sufficient promise. VCs are therefore naturally drawn to start-ups where early experiments are quicker and cheaper since it means their real option to reinvest or abandon at the next round is more valuable and the returns from their investments can be higher.

Ewens, Nanda, and Rhodes-Kropf, 2018 highlight how the introduction of cloud computing services dramatically lowered the cost of learning about the ultimate potential of risky web-based start-ups. Specifically, it allowed those start-ups to rent hardware in small increments from providers like Amazon Web Services, use this to quickly gauge customer demand, and postpone expensive investments to scale up until after learning about the size and nature of demand from consumers. This, in turn, led to a disproportionate rise in the number of start-ups that could benefit from such lowered cost of experimentation and faster experimentation cycles. Related to this, VC investors are often drawn to startups with limited technical risk and where the key uncertainty relates to market demand for the product or service. Rapid iteration around early customer validation can either show a lack of demand or help reduce market risk substantially, thereby making the initial de-risking cheap and efficient.

It is true that there is increasing scope for software and related information technologies to play a role in addressing climate and related challenges because products emerging from energy technologies are now more likely to be smaller, modular, and able to rely on innovation in high-tech sectors (Popp et al., 2020). However, our analysis of VC-backed Net Zero patents has also shown that the 'deep tech' patents that rely more on fundamental science are disproportionately related to startups in sectors such as semiconductors, computer hardware and industrial production. These are areas where early prototypes still embody substantial technical risk, where initial experiments involved in technical de-risking are expensive and do not always benefit from the faster experimentation cycles that VC investors are drawn to. This friction is consistent with the relative decline in such innovations coming from VC firms in recent years.

### 3.3.2 Learning Efficiency of Lab Experiments

When considering the role of experiments in early de-risking, it is also helpful to recognize that real options are more valuable in sectors where initial experiments *generate more information* —in other words, where achieving or missing initial milestones helps VCs learn more about the ultimate potential of a venture (Nanda and Rhodes-Kropf, 2016). This is because more informative experiments help VCs learn faster about firms that might ultimately fail, enabling them to "throw less good money after bad". More informative experiments also show firms achieving their promise earlier in their life, enabling start-ups to raise their next round of financing at much higher valuation step-ups. VCs who fund the initial rounds of financing in these ventures are therefore less diluted—that is, they maintain greater equity ownership—and hence generate a larger return for any given exit value.

Some of the challenges associated with deep tech commercialization stem from the fact that it is difficult to project how successful lab experiments might work at scale. For example, forecasting the unit costs – at scale – associated with energy storage using a new battery material or carbon capture and sequestration technology can be extremely difficult, even if the technology has been shown to work in a controlled laboratory environment. Moreover, since demand is tied to the ability of firms to produce at certain price points, this also implies that technology and market risk can often be intricately tied to each other in the energy sector (Arora, Fosfuri, and Roende, 2022). In such instances, the costs and timelines associated with the lower learning efficiency and de-risking process can be prohibitively large for commercial investors, as they may need to finance a full-scale demonstration pilots before learning whether the technology is sufficiently good to disrupt a market. The equity needed by a profit-seeking investor in such instances can be prohibitively large, leading projects with potential to not make it past the early de-risking phase.

Advances in digital chemistry and synthetic biology, as well as huge increases in computational power that enables more accurate simulation of material properties at scale, are helping to improve the ability to forecast from successful lab experiments to success at scale. However Siegmund et al., 2021 also point to the fact that lab experiments are often not conducted with a view to increasing learning efficiency. In the context of new catalysts, they point to specific examples of how success being defined on a different temperature, pressure and time-scale can lead to a large number of false positives – potential solutions that are deemed to be promising in lab experiments but could have been identified as having 'failed' in the lab if the thresholds used were more consistent with the requirements of at-scale commercial applications. Some of this is due to the fact that the early de-risking is increasingly done in university environments, where there can often be a lack of understanding of the specific industrial specifications or bottlenecks that need to be optimized in an industrial setting. Even within large organizations however, the R&D and product teams may not work to jointly set early-stage technical milestones in a manner that increases the information value of the early experiments.

### 3.3.3 Human Capital involved in Deep Tech translation

There are numerous challenges to building a new venture that faces large amounts of technical risk in addition to having to sell into highly regulated industries with large entrenched incumbents who are averse to adopting new technologies unless they have a huge economic benefit. This makes the challenge of having the right entrepreneurial talent to build such ventures and sell these products to commercial customers non-trivial (Nanda, Younge, and Fleming, 2014). Those with technical talent may not have the skill or inclination to get involved in commercialization, while those with entrepreneurial talent can find it hard to evaluate the quality of technical ideas at the nascent stages, making it unappealing to select into entrepreneurship for those with very high opportunity costs (Hall and Woodward, 2010). This is likely to be particularly true when the experimentation cycles and hence time to product is longer as is the case with many science-based deep tech ventures (Ewens, Nanda, and Stanton, 2020).

### 3.3.4 Appropriating Value being Created

The discussion above has focused on supply-side frictions that make it harder to reduce the technical, market and execution *risk* associated with building Deep Tech ventures relative to sectors such as information technology, software and services.

It is also the case that software ventures often have the potential to more easily generate *return*. One of the attractive features of information technology is the highly scalable and asset-light businesses it is associated with. This leads to high levels of profitability and more cash flow to investors per unit of revenue, which in turn creates enormous opportunities for outsized returns.

In many of the deep tech sectors such as energy generation, storage, capture and industrial production, new firms are typically selling to large incumbents with substantial market power and low willingness to adopt new technologies, thereby making it hard to command high profit margins when selling to them. Many of these customers could also be competitors, making it harder to appropriate value. Finally, to the extent that these require substantial investment in physical assets to generate cash, the path to becoming a valuable company can be slower. Indeed as Heuvel and Popp, 2022 note, a combination of 'lackluster demand and a lower potential for outsized returns' makes clean energy firms less attractive to venture capital investors.

## 3.4 Policy Implications

Having discussed some of the key frictions making Deep Tech investment less attractive to VC investors, we turn to a discussion of some policy implications. We note that innovation is clearly an important part of environmental policy, and encouraging innovation is often an explicit goal of policymakers. A large literature on the links between between environmental policy and innovation is beyond the scope of this paper (see for example, Popp, 2019 and (Fu et al., 2018)). Similarly, the speed required to develop Covid-19 vaccines underlines how much society depends on the pace of scientific research and how effective science funding can be. A bias against funding risky research has also been discussed in the literature (Franzoni, P. Stephan, and

Veugelers, 2021; P. Stephan, 2014) but we do not focus on this. We focus more narrowly on policies that might help address the specific sets of frictions outlined above that have been argued to reduce the risk-adjusted return of Deep Tech opportunities for VC investors.[13]

### 3.4.1 Government's role in stimulating demand

Many successful examples of government involvement in the commercialization of tough tech have been related to the government's role as a customer (Mowery, 2010; Mazzucato, 2013). A key reason for this may have to do with such advance market commitements substantially reducing market risk through a willingness to pay for early versions of an emerging technology. A large military contract can also help to establish standards and coordinate the direction of technology trajectories.

Mazzucato, 2013 notes the spillovers to ICT from NASA's decade-long mission to put a man on the moon. In a compelling case study of the iPhone, she also shows how several of its key components—GPS, touchscreen glass, accessibility of the Internet, and voice-recognition technology—benefited either directly or indirectly from state funding. Evidence has also been found that federal investment during World War II subsequently led to increased private sector investment. It is also suggested that a very substantial increase in federal investment in the life sciences and the growth of the biotechnology revolution was triggered by President Nixon's declaration of "War on Cancer" in 1971 and the substantial commitments to federal funding of biomedical science in the subsequent years through the National Institutes of Health.

Mowery, 2010 discusses the role of the U.S. military R&D and procurement budgets in driving substantial innovation and technological change in the United States in the post–World War II era. The government's role as a customer was very important in the 1960s and 1970s to the semiconductor industry—the one sector downstream from materials science where Venture Capitalists have profited at scale. The U.S. Department of Defense along with NASA played the role of collaborative customer, pulling the new industry down the learning curve to low cost, reliable production, as military customers had done for the preceding microelectronics industry up to and during World War II. Similarly, the U.S. government's role in reimbursement

[13] This section draws extensively on Janeway, Nanda, and Rhodes-Kropf, 2021.

of new drugs and devices through Medicare and Medicaid substantially reduces market risk for drug development, implying that biotechnology ventures have enjoyed very high rates of access to the IPO market, despite the very high degree of technology risk, the very long and expensive path to regulatory approval, and hence substantial cash flow deficits (Pisano, 2006). In the context of clean energy, Germany's role in committing to purchase electricity generated from renewable energy sources is likely to have played a role in driving the growth of the industry and bringing the solar-PV down. Paying part of the contract value in advance can substantially reduce start-ups' dependence on external finance. This important role of the government as customer is often underappreciated when considering the role that policymakers can play in jump-starting innovation.

Government's role as a customer can also be used in outlining property rights, particularly those that help to level the playing field for and enable innovation by start-ups. Program managers of the Defense Advanced Research Projects Agency (DARPA), especially in its early years when it was funding general-purpose IT-related research, conceived of their mission to include protection of the new entrants from the established incumbents (Azoulay et al., 2019). Related to this, strong intellectual property rights and a well functioning Markets for Technology (Arora, Belenzon, and Suh, 2021) helps startups motetize the value of their innovations.

### 3.4.2 Supporting Financing and Certification of Technical De-Risking

The record of government involvement in trying to directly subsidise the financing of startups has been mixed at best. Nevertheless, one setting where start-ups engaged in innovation have been shown to benefit substantially is the U.S. Department of Energy's SBIR grant program, which has helped start-ups finance the prototyping of new technologies and thereby substantially increase the odds of receiving venture capital (Lerner, 1999; S. T. Howell, 2017). This ties in directly to the friction outlined above—where start-ups in some sectors cannot attract VC due to the difficulty they face in learning about the effectiveness of a new technology in the field as opposed to the lab, and hence have trouble convincing investors they can achieve product-market fit and generate sufficient customer demand.

In the context of Net Zero innovations, organizations such as ARPA-E also play an important certification role in helping to vet promising technologies.

This can help provide independent validation that a technology is meeting technical milestones as VC and other commercial investors very often do not have the technical capability to assess and evaluate the efficacy and promise of a new technology.

### 3.4.3 Supporting New Organizational and Financing Models

As noted above, Deep Tech solutions to global challenges such as achieving Net Zero targets are increasingly being developed within universities. Many of the frictions noted above relate to the challenge of effective effective hand-off from a university lab environment to a commercial setting.

Given that they already have a lot of the specialized equipment, talent and technical expertise needed to support and validate technical de-risking, academic institutions have the potential to play a central role in helping to support the initial technical de-risking and development prior to start-ups raising risk capital from investors. Beyond cost, another potential key benefit of de-risking in a university environment is the potential to recycle knowledge arising from failure. Since most early stage experiments fail and the insights from the failure of such technical experiments is instructive for future generations of entrepreneurs, the different incentive system of a university related to scaling knowledge can be extremely valuable in this context, particularly in settings where there are strong externalities as is the case with knowledge around early stage de-risking and translation.

Another role that universities can play is in helping founders of deep tech ventures, who often have technical background but less business training, to understand the appropriate customer segments, business models, and financing sources for their new ventures (Cohen, Sauermann, and P. Stephan, 2020; Sauermann and P. E. Stephan, 2010). In addition to helping to stimulating the supply of technical talent that is also trained for building ventures, universities can play a role in helping to match strong technical projects with similarly strong entrepreneurial talent.

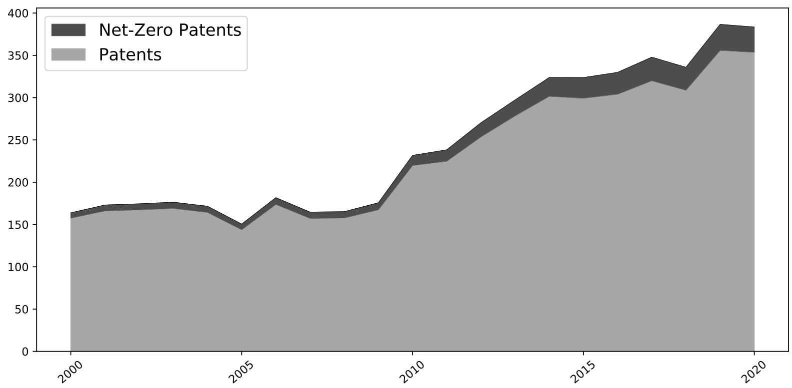
In terms of the transition from universities to Venture Capital, VC firms typically raise closed-end funds, implying that they are required to invest the money they raise and return the proceeds within a fixed period, usually 10 years. Given that investments are made over the first few years, this implies that VCs are naturally drawn to investments where they can realize a return through an exit—either an acquisition or an IPO—within a short time. Not all ventures are amenable to this timeline. For example, start-ups that have a physical component to generating cash flows often take longer to build, particularly if the venture needs to build factories to produce new products—as is the case with energy production, storage and many industrial production methods. Although VCs have some leeway to extend the fund life a few years, the fixed limit to a fund's life can become a binding constraint for investors, although the use of evergreen funds can overcome such constraints Lerner and Nanda, 2020.

As noted by Nanda, Samila, and Sorenson, 2020, universities, government labs, corporate R&D, VC firms, corporate venture capital firms, and longer-term "patient capital" associated with family offices each bring different incentives, funding models, ability to experiment, and tolerance for failure. Each has different benefits and constraints. Understanding the degree to which these can be adapted to most effectively help commercialize Deep Tech addressing Net Zero Challenges —perhaps while also harnessing non-dilutive capital from philanthropy for initial experiments—is a promising area of further inquiry.

## 3.5 Figures and Tables

FIGURE 3.1: **Level and Growth of USPTO Patents from 2000-2020** This figure shows the number of Net-Zero and all other patents granted by the USPTO from 2000 to 2020 (Panel A). Net-Zero patents include the six groups identified using the CPC classification system and reported in Table 1. Panel B reports the growth of these two groups, relative to the number of patents in each group in 2000.

*Panel A: Granted Patents - Levels (in thousands)*




*Panel B: Granted Patents - Relative Growth*

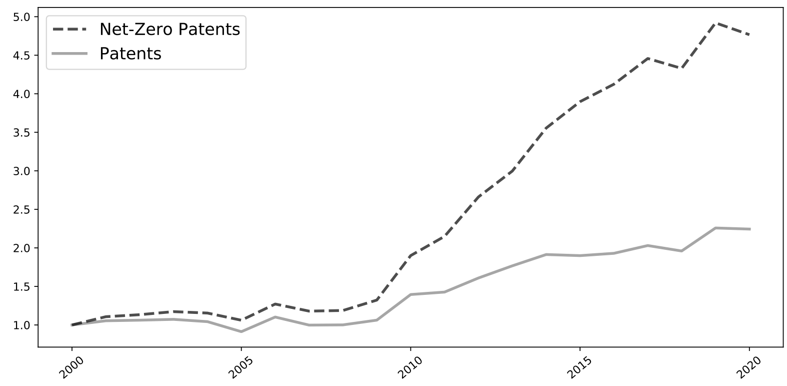
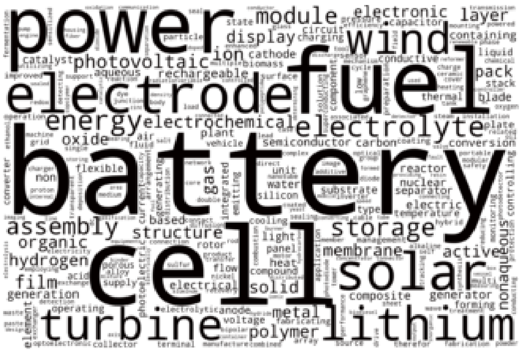
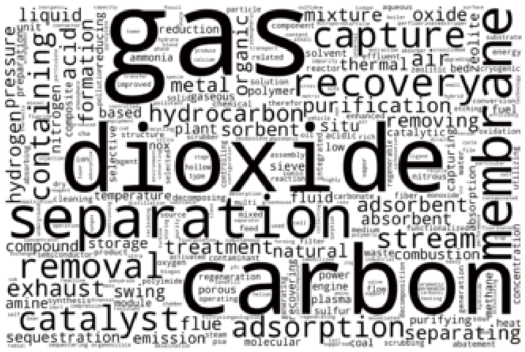


FIGURE 3.2: **Distinctive Words in each Category of Net Zero Patents granted between 2000 and 2020** This figure uses text taken from the titles of all Net Zero patents to identify distinctive words associated with each Net Zero sub-category. The distinct words associated with each category are derived using a TF-IDF procedure, where the frequency of each word in a document (TF) is weighted by the inverse of the frequency of all documents in the corpus (IDF).

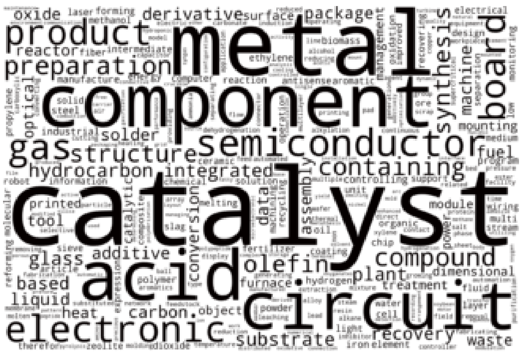
*Panel A: Generation and Storage*



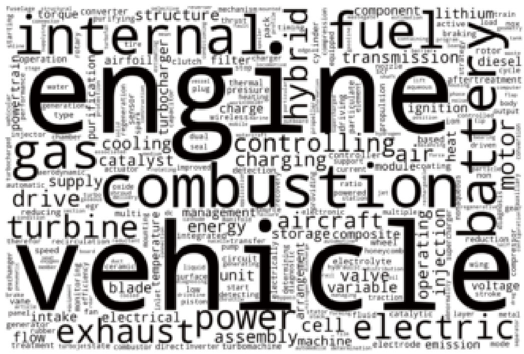

*Panel B: GHG Capture*



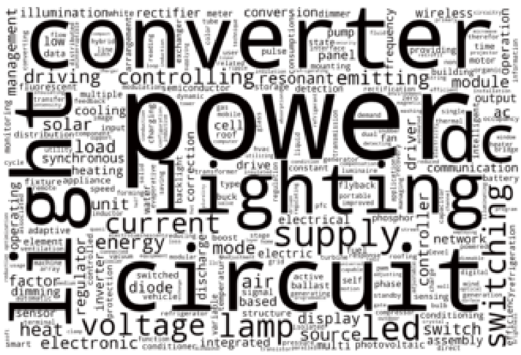

*Panel C: Mitigation in Industrial Production*




*Panel D: Mitigation in Transport*



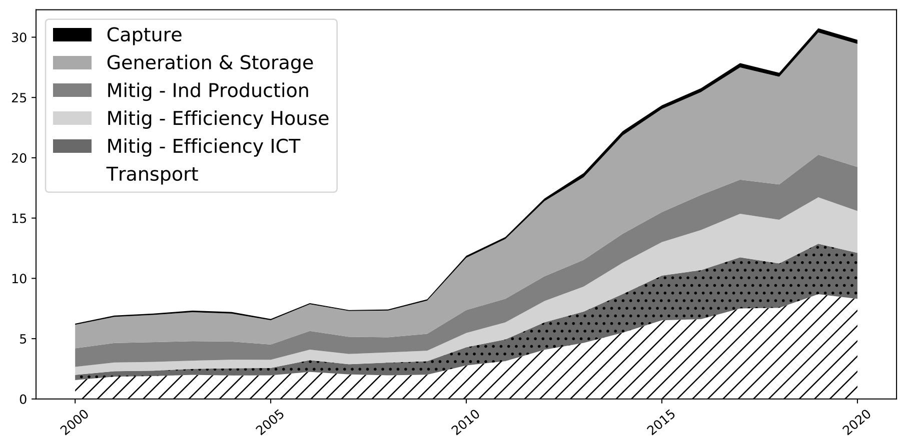

*Panel E: Energy Efficiency in Buildings*




*Panel F: Energy Efficiency in ICT*

FIGURE 3.3: **Level and Growth of Net Zero Patents from 2000-2020, by Category** This figure reports details on Net Zero patents granted by the USPTO from 2000 to 2020, by the six Net-Zero categories used in this paper. The six Net-Zero groups are identified using the CPC classification tagging system, and they are: energy Generation & Storage (class Y02E in Table 3.1), technologies for GHG Capture (class Y02C in Table 3.1), technologies for mitigation in industrial production (class Y02P in Table 3.1), technologies related to transportation (class Y02T in Table 3.1), technologies related to energy efficiency in buildings (class Y02B in Table 3.1) and in ICT (class Y02D in Table 3.1). Panel A is a stacked chart that reports the overall number of patents in each class, Panel B reports the growth of these groups, relative to the number of patents in each group in 2000.

*Panel A: Number of Green Patents by Cleantech Class (in thousands)*




*Panel B: Relative Growth of Green Patents by Cleantech Class*

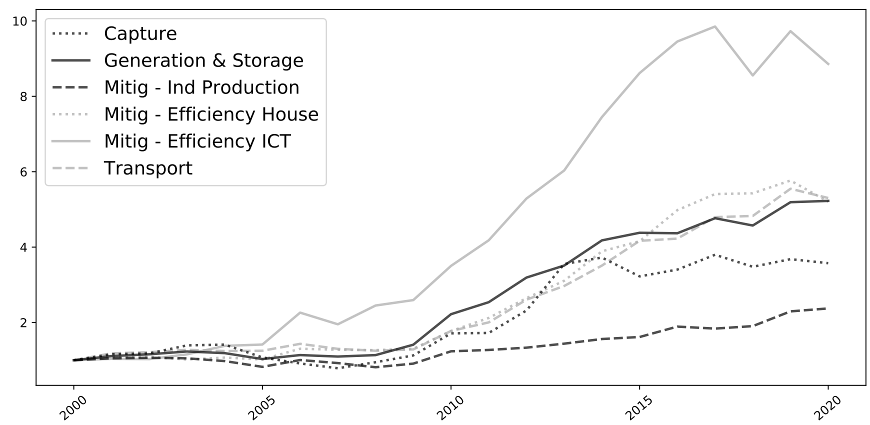


FIGURE 3.4: **Share of Net-Zero Patents that are Deep Tech, by Assignee Type** This figure reports the share of Net-Zero patents that are classified as deep technologies, by assignee type over the 2000-2020 time period. Deep technologies are identified using patents to science citations as described in Table 3.2, and this group includes: energy generation and storage, GHG mitigation in industrial production, and carbon capture technologies.

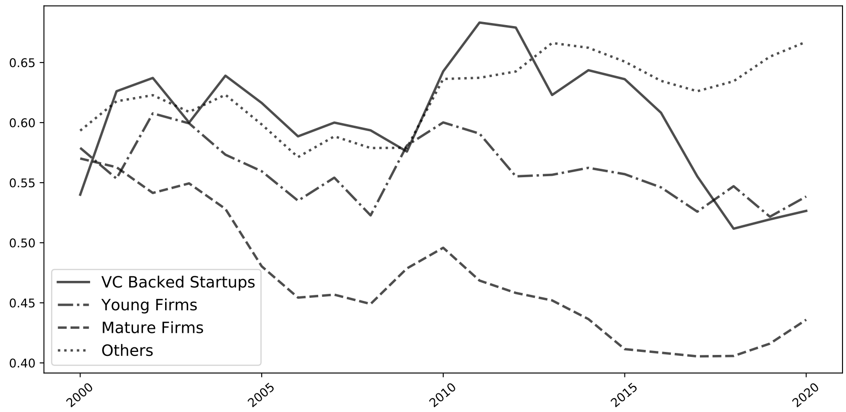


TABLE 3.1: **Cooperative Patent Classification of 'Green Innovations'** This table reports the description of different CPC classification groups used to tag green innovation. As can be seen from the Table, green patents include the categories Y02A and Y02W, but these have been excluded from our analysis as the focus of this paper is on technologies who can directly contribute to meeting Net-Zero targets.

| | |
|---|---|
| **Y02E** | **REDUCTION OF GREENHOUSE GAS [GHG] EMISSIONS, RELATED TO ENERGY GENERATION, TRANSMISSION OR DISTRIBUTION** |
| 10/00 | Energy generation through renewable energy sources |
| 30/00 | Energy generation of nuclear origin |
| 20/00 | Combustion technologies with mitigation potential |
| 40/00 | Technologies for an efficient electrical power generation, transmission or distribution |
| 50/00 | Technologies for the production of fuel of non-fossil origin |
| 60/00 | Enabling technologies;Technologies with a potential or indirect contribution to GHG emissions mitigation |
| 70/00 | Other energy conversion or management systems reducing GHG emissions |
| **Y02C** | **CAPTURE, STORAGE, SEQUESTRATION OR DISPOSAL OF GREENHOUSE GASES [GHG]** |
| 20/00 | Capture or disposal of greenhouse gases |
| 20/10 | of nitrous oxide (N20) |
| 20/20 | of methane |
| 20/30 | of perfluorocarbons [PFC], hydrofluorocarbons [HFC] or sulfur hexafluoride [SF6] |
| 20/40 | of CO2 |
| **Y02P** | **CLIMATE CHANGE MITIGATION TECHNOLOGIES IN THE PRODUCTION OR PROCESSING OF GOODS** |
| 10/00 | Technologies related to metal processing |
| 20/00 | Technologies relating to chemical industry |
| 30/00 | Technologies relating to oil refining and petrochemical industry |
| 40/00 | Technologies relating to the processing of minerals |
| 60/00 | Technologies relating to agriculture, livestock or agroalimentary industries |
| 70/00 | Climate change mitigation technologies in the production process for final industrial or consumer products |
| 80/00 | Climate change mitigation technologies for sector-wide applications |
| 90/00 | Enabling technologies with a potential contribution to greenhouse gas [GHG] emissions mitigation |
| **Y02T** | **CLIMATE CHANGE MITIGATION TECHNOLOGIES RELATED TO TRANSPORTATION** |
| 10/00 | Road transport of goods or passengers |
| 30/00 | Transportation of goods or passengers via railways, e.g. energy recovery or reducing air resistance |
| 50/00 | Aeronautics or air transport |
| 70/00 | Maritime or waterways transport |
| 90/00 | Enabling technologies or technologies with a potential or indirect contribution to GHG emissions mitigation |
| **Y02B** | **CLIMATE CHANGE MITIGATION TECHNOLOGIES RELATED TO BUILDINGS, e.g. HOUSING, HOUSE APPLIANCES OR RELATED END-USER APPLICATIONS** |
| 10/00 | Integration of renewable energy sources in buildings |
| 20/00 | Energy efficient lighting technologies, e.g. halogen lamps or gas discharge lamps |
| 30/00 | Energy efficient heating, ventilation or air conditioning [HVAC] |
| 40/00 | Technologies aiming at improving the efficiency of home appliances, e.g. induction cooking or efficient technologies for refrigerators, freezers or dish washers |
| 50/00 | Energy efficient technologies in elevators, escalators and moving walkways, e.g. energy saving or recuperation technologies |
| 70/00 | Technologies for an efficient end-user side electric power management and consumption |
| 80/00 | Architectural or constructional elements improving the thermal performance of buildings |
| 90/00 | Enabling technologies or technologies with a potential or indirect contribution to GHG emissions mitigation |
| **Y02D** | **CLIMATE CHANGE MITIGATION TECHNOLOGIES IN INFORMATION AND COMMUNICATION TECHNOLOGIES [ICT], I.E. INFORMATION AND COMMUNICATION TECHNOLOGIES AIMING AT THE REDUCTION OF THEIR OWN ENERGY USE** |
| 10/00 | Energy efficient computing, e.g. low power processors, power management or thermal management |
| 30/00 | Reducing energy consumption in communication networks |
| **Y02A** | **TECHNOLOGIES FOR ADAPTATION TO CLIMATE CHANGE** |
| 10/00 | at coastal zones; at river basins |
| 20/00 | Water conservation; Efficient water supply; Efficient water use |
| 30/00 | Adapting or protecting infrastructure or their operation |
| 40/00 | Adaptation technologies in agriculture, forestry, livestock or agroalimentary production |
| 50/00 | in human health protection, e.g. against extreme weather |
| 90/00 | Technologies having an indirect contribution to adaptation to climate change |
| **Y02W** | **CLIMATE CHANGE MITIGATION TECHNOLOGIES RELATED TO WASTEWATER TREATMENT OR WASTE MANAGEMENT** |
| 10/00 | Technologies for wastewater treatment |
| 30/00 | Technologies for solid waste management |
| 90/00 | Enabling technologies or technologies with a potential or indirect contribution to greenhouse gas [GHG] emissions mitigation |

TABLE 3.2: **Citation to fundamental science by Net Zero patents, by Category** This table reports the propensity to cite science for Net Zero patents and heterogeneity across sub-categories. Column 2 reports the share of Net-Zero patents that cite at least 1 scientific article for each category. Columns 3-8 report the intensity of scientific citations by category, conditional on citing at least one scientific paper. Data on scientific citations are obtained through the open-source dataset provided by Marx and Fuegi, 2020. Citations include front-page citations to scientific papers as described in section 3.2. Energy generation and storage, GHG capture and technologies for Mitigation in Industrial Production cite science more intensively and hence are labeled as 'Deep Tech'.

| | | # Patents | % with 1 or more scientific citations | Mean | p10 | p25 | p50 | p75 | p90 |
|---|---|---|---|---|---|---|---|---|---|
| | GHG Capture | 4,248 | 48% | 13 | 1 | 2 | 4 | 10 | 37 |
| Deep Tech | Mitigation in Industrial Prod. | 43,641 | 39% | 12 | 1 | 1 | 4 | 10 | 28 |
| | Generation and Storage | 108,691 | 33% | 11 | 1 | 1 | 3 | 9 | 24 |
| | Energy Efficiency in ICT | 42,053 | 29% | 7 | 1 | 1 | 2 | 5 | 14 |
| Non Deep Tech | Energy Efficiency in Buildings | 37,358 | 18% | 6 | 1 | 1 | 2 | 5 | 13 |
| | Mitigation in Transport | 84,843 | 12% | 7 | 1 | 1 | 2 | 5 | 13 |

TABLE 3.3: **Net Zero Patenting by Sector and Assignee Type** The first two columns of this table document the number and share of Net Zero patents that are associated with different assignee types. Columns 3 to 8 report the share of each assignee-type's patents that correspond to each sector. For example, 45.5% of VC-backed startup patents are related to Generation & Storage, while 1.3% of mature firm patents are related to GHG Capture.

| | | | Share of Total Patents of each Assignee in each Class | | | | | |
|---|---|---|---|---|---|---|---|---|
| | # of tot patents | % of tot patents | Generation & Storage | GHG Capture | Mitigation in Industrial Prod. | Mitigation in Transport | Energy Eff. in Buildings | Energy Eff. in ICT |
| VC Backed Startups | 8,806 | 2.6% | 45.5% | 0.6% | 13.9% | 11.6% | 13.9% | 14.5% |
| Young Firms | 70,001 | 20.8% | 38.7% | 1.2% | 15.6% | 21.6% | 14.3% | 8.4% |
| Mature Firms | 218,417 | 64.8% | 30.4% | 1.3% | 12.6% | 29.9% | 10.2% | 15.5% |
| Others | 39,935 | 11.8% | 45.9% | 2.0% | 15.6% | 19.9% | 12.0% | 4.5% |

TABLE 3.4: **Citation to Science associated with different Assignee types** This table reports differences in propensity to cite science by patents granted to different assignee types. Columns report results for all patents in the USPTO database from 2000-2020 and separately for Net Zero, Deep Tech and Non-Deep Tech patents and defined in Table 3.2. Data on scientific citations are obtained through the open-source dataset provided by Marx and Fuegi, 2020.

*Panel A: Unconditional mean of citations to science*

| | All Patents | Net-Zero Patents | Net-Zero Deep Tech | Net-Zero Non DT |
|---|---|---|---|---|
| VC Backed Startups | 11.6 | 12.4 | 17.3 | 5.0 |
| Young Firms | 3.6 | 2.9 | 4.2 | 1.3 |
| Mature Firms | 3.1 | 2.2 | 3.7 | 1.0 |
| Others | 3.9 | 2.5 | 3.4 | 1.1 |

*Panel B: Conditional on having at least one citation to science*

| | All Patents | Net-Zero Patents | Net-Zero Deep Tech | Net-Zero Non DT |
|---|---|---|---|---|
| VC Backed Startups | 23.3 | 24.4 | 29.7 | 12.7 |
| Young Firms | 13.6 | 10.6 | 12.1 | 7.0 |
| Mature Firms | 11.3 | 9.0 | 10.9 | 6.0 |
| Others | 13.8 | 4.0 | 8.3 | 6.0 |

TABLE 3.5: **Patent Impact by Assignee Type** This table reports the share of each assignee's patents that are in the top 10% (Panel A) and top 1% (Panel B) of influential patents, normalized within a given grant year and USPTO technology class. The sample includes patents granted from 2000-2017 as patents granted extremely recently have not accumulated sufficient number of citations to accurately identify outliers.

*Panel A: Share of Patents being in the top 10% of Citations Received*

| | All Patents | Net-Zero Patents | Net-Zero Deep Tech | Net-Zero Non DT |
|---|---|---|---|---|
| VC Backed Startups | 21.4% | 27.3% | 23.6% | 33.4% |
| Young Firms | 10.6% | 13.3% | 11% | 16.3% |
| Mature Firms | 9% | 10.2% | 8.8% | 11.5% |
| Others | 6.9% | 9.7% | 8.1% | 12.5% |

*Panel B: Share of Patents being in the top 1% of Citations Received*

| | All Patents | Net-Zero Patents | Net-Zero Deep Tech | Net-Zero Non DT |
|---|---|---|---|---|
| VC Backed Startups | 2.9% | 4.6% | 3.7% | 6% |
| Young Firms | 1.1% | 1.6% | 1.2% | 2% |
| Mature Firms | 0.9% | 1.0% | 1.1% | 1% |
| Others | 0.6% | 0.9% | 0.6% | 1.2% |

## References

Akcigit, Ufuk and William R. Kerr (2018). “Growth through Heterogeneous Innovations”. In: *Journal of Political Economy* 126.4, pp. 1374–1443.

Arora, Ashish, Sharon Belenzon, and Andrea Patacconi (2018). “The decline of science in corporate R&D”. In: *Strategic Management Journal* 39.1, pp. 3–32.

Arora, Ashish, Sharon Belenzon, Andrea Patacconi, and Jungkyu Suh (2020). “The Changing Structure of American Innovation: Some Cautionary Remarks for Economic Growth”. In: *Innovation Policy and the Economy* 20.1, pp. 39–93.

Arora, Ashish, Sharon Belenzon, and Jungkyu Suh (Mar. 2021). *Science and the Market for Technology*. Working Paper 28534. National Bureau of Economic Research.

Arora, Ashish, Andrea Fosfuri, and Thomas Roende (Jan. 2022). *Caught In The Middle: The Bias Against Startup Innovation With Technical And Commercial Challenges*. Working Paper 29654. National Bureau of Economic Research.

Azoulay, Pierre et al. (2019). “Funding Breakthrough Research: Promises and Challenges of the ARPA Model”. In: *Innovation Policy and the Economy* 19, pp. 69–96.

Bernstein, Shai, Xavier Giroud, and Richard R. Townsend (2016). “The impact of venture capital monitoring”. In: *The Journal of Finance* 71.4, pp. 1591–1622.

Cohen, Wesley M., Henry Sauermann, and Paula Stephan (2020). “Not in the Job Description: The Commercial Activities of Academic Scientists and Engineers”. In: *Management Science* 66.9, pp. 4108–4117.

Cunningham, Colleen, Florian Ederer, and Song Ma (2021). “Killer Acquisitions”. In: *Journal of Political Economy* 129.3, pp. 649–702.

Ewens, Michael, Ramana Nanda, and Matthew Rhodes-Kropf (2018). “Cost of experimentation and the evolution of venture capital”. In: *Journal of Financial Economics* 128.3, pp. 422–442.

Ewens, Michael, Ramana Nanda, and Christopher T. Stanton (June 2020). *The Evolution of CEO Compensation in Venture Capital Backed Startups*. NBER Working Papers. National Bureau of Economic Research, Inc.

Franzoni, Chiara, Paula Stephan, and Reinhilde Veugelers (June 2021). *Funding Risky Research*. Working Paper 28905. National Bureau of Economic Research.

Fu, Wancong et al. (Dec. 2018). *Technological Spillover Effects of State Renewable Energy Policy: Evidence from Patent Counts*. Working Paper 25390. National Bureau of Economic Research.

Hall, Robert E. and Susan E. Woodward (June 2010). "The Burden of the Nondiversifiable Risk of Entrepreneurship". In: *American Economic Review* 100.3, pp. 1163–94.

Haščič, Ivan and Mauro Migotto (2015). "Measuring environmental innovation using patent data". In: *OECD Environment Working Papers* 89.

Heuvel, Matthias van den and David Popp (Apr. 2022). *The role of Venture Capital and Governments in Clean Energy: Lessons from the First Cleantech Bubble*. Working Paper 29919. National Bureau of Economic Research.

Howell, Sabrina et al. (2020). "How resilient is venture-backed innovation? Evidence from four decades of U.S. patenting". In: *NBER Working Paper*.

Howell, Sabrina T. (Apr. 2017). "Financing Innovation: Evidence from R&D Grants". In: *American Economic Review* 107.4, pp. 1136–64.

Janeway, William H., Ramana Nanda, and Matthew Rhodes-Kropf (2021). "Venture Capital Booms and Start-Up Financing". In: *Annual Review of Financial Economics* 13.1, pp. 111–127.

Kerr, William R., Ramana Nanda, and Matthew Rhodes-Kropf (2014). "Entrepreneurship as Experimentation". In: *Journal of Economic Perspectives* 28.3, pp. 25–48.

Kortum, Samuel and Josh Lerner (2000). "Assessing the Contribution of Venture Capital to Innovation". In: *The RAND Journal of Economics* 31.4, pp. 674–692.

Lerner, Josh (1999). "The Government as Venture Capitalist: The Long-Run Impact of the SBIR Program". In: *The Journal of Business* 72.3, pp. 285–318.

Lerner, Josh and Ramana Nanda (2020). "Venture Capital's Role in Financing Innovation: What We Know and How Much We Still Need to Learn". In: *Journal of Economic Perspectives* 34.3, pp. 237–261.

Marx, Matt and Aaton Fuegi (2020). "Reliance on science: Worldwide front-page patent citations to scientific articles". In: *Strategic Management Journal* 41, pp. 1572–1594.

— (2021). "Reliance on science: Worldwide front-page patent citations to scientific articles". In: *Journal of Economic and Management Strategy* 31, pp. 369–392.

Mazzucato, Mariana (2013). *The entrepreneurial state : debunking public vs. private sector myths*. Anthem frontiers of global political economy. Anthem Press.

Mowery, David C. (2010). "Military R&D and Innovation". In: *Handbook of the Economics of Innovation, Volume 2*. Ed. by Bronwyn H. Hall and Nathan Rosenberg. Vol. 2. Handbook of the Economics of Innovation. North-Holland, pp. 1219–1256.

Nanda, Ramana and Matthew Rhodes-Kropf (2016). "Financing Entrepreneurial Experimentation". In: *Innovation Policy and the Economy* 16.1, pp. 1–23.

Nanda, Ramana, Sampsa Samila, and Olav Sorenson (2020). "The persistent effect of initial success: Evidence from venture capital". In: *Journal of Financial Economics* 137.1, pp. 231–248.

Nanda, Ramana, Ken Younge, and Lee Fleming (Apr. 2014). "Innovation and Entrepreneurship in Renewable Energy". In: *The Changing Frontier: Rethinking Science and Innovation Policy*. NBER Chapters. National Bureau of Economic Research, Inc, pp. 199–232.

"Net Zero by 2050 - A Roadmap for the Global Energy Sector" (2022). In: *International Energy Agency*. URL: https://www.iea.org/reports/net-zero-by-2050.

Pisano, Gary P. (2006). *Science Business: The Promise, the Reality, and the Future of Biotech*. Boston: Harvard Business School Press.

Popp, David (Mar. 2019). *Environmental Policy and Innovation: A Decade of Research*. Working Paper 25631. National Bureau of Economic Research.

Popp, David et al. (May 2020). *Innovation and Entrepreneurship in the Energy Sector*. Working Paper 27145. National Bureau of Economic Research.

Reinganum, Jennifer F (Sept. 1983). "Uncertain Innovation and the Persistence of Monopoly". In: *American Economic Review* 73.4, pp. 741–748.

Sauermann, Henry and Paula E Stephan (June 2010). *Twins or Strangers? Differences and Similarities between Industrial and Academic Science*. Working Paper 16113. National Bureau of Economic Research.

Siegmund, Daniel et al. (2021). "Crossing the Valley of Death: From Fundamental to Applied Research in Electrolysis". In: *JACS Au* 1.5, pp. 527–535.

Stephan, Paula (July 2014). "The Endless Frontier: Reaping What Bush Sowed?" In: *The Changing Frontier: Rethinking Science and Innovation Policy*. University of Chicago Press, pp. 321–366.