**Essays on Financial and Technological Innovations, Private Capital Markets, and Entrepreneurship**

by

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## Dedication

I would like to express my heartfelt dedication of my dissertation to my family. I am immensely grateful to my loving parents and my dear brother for their unwavering support throughout this transformative journey. To my mother, who has not only been my closest confidante but also a pillar of strength, offering unwavering support throughout the years. And to my father, whose nurturing of my curiosity in learning began during my elementary school years through his assistance with preliminary physics experiments, and who continued to answer my questions in physics and mathematics from middle school all the way to university. To my brother, whose unwavering belief in my potential propelled me forward, and who stood as one of the very few individuals who encouraged me to step out of my comfort zone and pursue my dreams beyond the borders of my home country. Their collective love, guidance, and encouragement have played an instrumental role in shaping my academic path, and for that, I am eternally grateful.

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**Abstract**

Access to financing is one of the main barriers to entrepreneurial activities and economic growth. In my research, I investigate whether financial and technological innovations mitigate frictions in the market for early-stage financing and spur economic activity.

In Chapter 1, I study whether access to return-based crowdfunding decreases the importance of local financial market development for entrepreneurial activities. Using both the staggered adoption of intrastate equity crowdfunding across U.S. states and the 2016 passage of Regulation CF, I find that access to crowdfunding increases the number of business applications, and this effect is stronger in states where local financial markets are less developed. I also find that by reducing local bias in entrepreneurship, intrastate crowdfunding benefits entrepreneurs who work in states where they were not born. Interestingly, intrastate crowdfunding, but not Regulation CF, increases the number of business applications that turn into employer businesses. While intrastate crowdfunding increases job creation and self-employment and decreases job destruction, Regulation CF decreases establishment entry and exit.

In Chapter 2, my co-authors and I investigate whether access to online communication technologies can decrease the importance of geographical proximity in acquiring soft information. To answer this question, we focus on the VC industry because lack of hard information on start-ups makes this industry heavily reliant on soft information and as a result on in-person interactions. We investigate how the sudden interruption in in-person meetings due to Covid-19 affected VC's deal selection, monitoring, and deal syndication. We find that VCs invest in farther away companies; However the changes we observe in characteristics of portfolio companies, in monitoring practices, and in forming syndications suggest that access to on-line

communications cannot eliminate the frictions caused by distance between VCs and their portfolio companies in acquiring soft information.

In Chapter 3, using a hand-collected data set on the Regulation A+ filings, I provide detailed information on the age, size, number of employees, financial statement items, and industrial and geographical distributions of companies that use Regulation A+. Testing the effect of Regulation A+ on the local economy, I find that the amount raised through this method of financing is negatively associated with ensuing unemployment rate. In addition, I investigate whether this new method of financing is substituting or complementing venture capital (VC) financing. The data analysis shows that Regulation A+ facilitates access to financing in regions and industries that could not attract VC-financing ex-ante. Finally, I find evidence consistent with successful Regulation A+ offerings in a region attracting ensuing VC investments through decreasing uncertainty and search cost.

Overall, my dissertation demonstrates that financial and technological innovations increase access to financing and spur entrepreneurial activities more in less developed regions. As a result, they can mitigate the discrepancies in entrepreneurial activities and economic growth across the U.S.

# Chapter 1. Return-based Crowdfunding and Entrepreneurship

## 1.1 Introduction

Entrepreneurship plays an important role in the process of creative destruction, economic growth, and job creation (King and Levine, 1993a,b; Levine, 1997; Levine and Zervos, 1998; Haltiwanger et al., 2013). One of the biggest barriers to entrepreneurial activities is access to capital (Kerr and Nanda, 2011). Because of financing frictions, local financial market development can play an important role for entrepreneurship and economic growth, even in well-developed and integrated financial markets (Jayaratne and Strahan, 1996; Dehejia and Lleras-Muney, 2003; Guiso et al., 2004; Nguyen, 2019). For example, the literature shows that in regions with more developed local financial markets, the entry and growth of new firms and the propensity of individuals to start new businesses are higher (Guiso et al., 2004; Kerr and Nanda, 2009). Moreover, these effects are more significant for small firms because high levels of uncertainty and information asymmetry can make it harder for them to access financing outside of their local areas (Guiso et al., 2004).

Innovations in the financial sector can help reduce the effect of local financial market development on entrepreneurship. A prominent example of such innovations is return-based crowdfunding, which is an online method of financing private ventures from the crowd through the issuance of equity or debt. This method of financing is unique in that retail (non-accredited) investors can invest in private firms. In this paper, I examine whether access to return-based crowdfunding decreases the importance of local financial market development for entrepreneurial activities. I show that return-based crowdfunding regulations mitigate the effect of local financial market development on business initiation and spur entrepreneurial activities. However, my results also show that state-level and federal-level return-based crowdfunding regulations have very different effects on employer business formation and dynamics and real economic outcomes, suggesting that frictions such as information asymmetry continue to play an important role for this method of financing as well.

Access to return-based crowdfunding can make local financial market development less important for entrepreneurs and small businesses for two reasons: 1) it provides a source of capital outside of entrepreneurs' local areas; and 2) crowdfunding platforms decrease search costs for investors.[1] However, given the high level of uncertainty and information asymmetry surrounding businesses that use return-based crowdfunding and the fact that many investors in return-based crowdfunding campaigns are not professional investors, it is possible that return-based crowdfunding does not provide entrepreneurs with a viable source of financing. Many commentators have expressed the view that the risk of fraud, the riskiness of these investments, and the possibility that low-quality businesses use return-based crowdfunding would deter individuals from investing in these campaigns. For example, according to the founder and CEO of the crowdfunding service Wefunder, "Small business owners that have ambition and intend to grow are less likely to crowdfund. Unaccredited investors can only invest in companies that don't have dreams to grow. Adverse selection at its finest."[2] Similarly, Catalini et al. (2016) argue that return-based crowdfunding is not likely to provide average investors (non-accredited investors) with the chance to fund the "next great idea" and that return-based crowdfunding platforms need to improve their market design rules if they want to attract higher-quality startups.

To study whether access to return-based crowdfunding reduces the role of local financial market development in entrepreneurship, I examine the effects of return-based crowdfunding regulations in the United States at both the state level and the federal level. In particular, I use the staggered adoption of intrastate crowdfunding by 35 states/territories in the U.S. and the 2016 passage of Regulation Crowdfunding (Title III of the JOBS Act) at the

[1] For example, Kerr and Nanda (2011) write: "Thus, innovations within the financial sector that lower information costs can have important effects on reducing financing constraints for entrepreneurs."

[2] See https://www.crowdfundinsider.com/2015/11/76979-wefunder-to-sec-title-iii-critical-aw-harms-investors/. See also https://www.sec.gov/comments/jobs-title-iii/jobstitleiii- 260.htm for a discussion of potential fraud by the SEC and The *New York Times* article "S.E.C. Gives Small Investors Access to Equity Crowdfunding" from October 31, 2015 for other skeptical views.

federal level as empirical settings to test the differential effect of access to return-based crowdfunding across states depending on the depth of local financial markets. These regulations allow average (non-accredited) investors to invest in private firms and exempt firms from registration with the SEC and state regulators before issuing securities. Intrastate crowdfunding allows issuers to raise capital only from the residents of the state where their principal place of business is located. By contrast, Regulation Crowdfunding (Regulation CF) allows them to raise capital from all interested investors. The financing limit under Regulation CF was $1.07 million over the 2009-2019 sample period, whereas the financing limit under intrastate crowdfunding differs across the U.S. states and ranges from $1 million to an unlimited amount.

I use the Business Formation Statistics (BFS) dataset provided by the U.S. Census Bureau to study the changes in business initiation after the passage of return-based crowdfunding regulations over the 2009-2019 sample period. In particular, the BFS dataset provides information on the number of business applications for tax IDs. Studying this outcome variable helps understand whether or not entrepreneurs perceive access to crowdfunding to be helpful in establishing a business. However, I also examine whether these businesses actually survive and turn into employer businesses using business formation measures in subsequent tests described below (business formation measures show how many of the business applications turn into employer businesses within one or two years after business applications are filed.)

Following King and Levine (1993a) and Kerr and Nanda (2009), I consider five measures of state-level financial market development: the number and dollar volume of loans with origination amounts less than or equal to $1 million; the number and dollar volume of loans to businesses with annual revenues less than or equal to $1 million (all four from the Community Reinvestment Act (CRA) data); and the level of bank deposits reported by the Federal Deposit Insurance Corporation (FDIC). My results are broadly robust across all these measures.

My main results show that both intrastate crowdfunding and Regulation CF have a positive and significant effect on the total number of business applications. Moreover, this effect is larger in states with less developed local financial markets. For example, the number of business applications in a state with an average pre-treatment amount of loans to small businesses increases by 2% after the passage of intrastate crowdfunding laws and by 35.7% after the passage of Regulation CF. A 10% decrease in the pre-treatment amount of loans to small businesses increases the effect of intrastate crowdfunding by 0.62% and the effect of Regulation CF by 0.40%.

The increase in the total number of business applications after the passage of return-based crowdfunding laws suggests that entrepreneurs perceive return-based crowdfunding as a viable method of financing, and, as a result, become motivated to pursue entrepreneurial activities. Regulation CF has a much stronger effect on spurring entrepreneurial activities than intrastate crowdfunding. This could be because the passage of Regulation CF at the federal level provides access to a larger pool of potential investors than the passage of intrastate crowdfunding laws. In addition, issuers who want to use intrastate crowdfunding should satisfy at least one “doing business" requirement under Rule 147 (more recently Rule 147A) to prove the in-state nature of the business.[3] Satisfying these requirements strongly limits the operation of a business to the state where it wants to use intrastate crowdfunding and may prevent some entrepreneurs from considering this method of financing.

There are two types of firms that could benefit from access to return-based crowdfunding: corporations and non-corporations (such as sole-proprietorships, partnerships, and limited liability companies). Studying these subsamples of business applications using the BFS dataset, I find that both intrastate crowdfunding and Regualtion CF have a particularly strong effect on the number of business applications by non-corporations. These positive effects are stronger in states with less developed financial markets. In Section 1.5.2, I discuss several possible reasons why return-based crowdfunding can alleviate the frictions in access to financing for this group of firms.

[3] In particular, the issuers have to satisfy at least one of the following requirements to be deemed to be doing business within a state or territory: (1) at least 80% of consolidated gross revenue of the issuer originates from operations or rendering services in that state; (2) at least 80% of issuer's assets and those of its subsidiaries on a consolidated basis are located in that state; (3) the issuer intends to use at least 80% of crowdfunding campaign net proceeds in relation to operations or rendering services in that state; (4) a majority of the issuer's employees are based in that state.

Next, I investigate whether return-based crowdfunding can help alleviate constraints uniquely faced by non-local entrepreneurs. Michelacci and Silva (2007) show that individuals who work in states where they were born (locals) are more likely to be entrepreneurs and that local financial market development benefits local entrepreneurs more than non locals. They call this phenomenon local bias in entrepreneurship (LBE).[4] The presence of the LBE suggests that entrepreneurship may not be a mobile factor of production that gets optimally allocated to take advantage of technological differences. I therefore examine whether return-based crowdfunding can alleviate the LBE, i.e., whether it increases the probability that entrepreneurs start businesses in states where they were not born.

It is a priori unclear whether access to return-based crowdfunding will increase or decrease the LBE. On the one hand, it may decrease the LBE because it provides entrepreneurs with a source of financing outside of their local area and crowdfunding investors may not consider where the entrepreneur is born. On the other hand, high information asymmetry and uncertainty surrounding crowdfunding campaigns may encourage investors to invest locally (Hornuf et al., 2020). I find that the local bias in entrepreneurship decreases after the passage of intrastate crowdfunding. This observation suggests that intrastate crowdfunding investors are more willing to invest in startups by non-locals that they find viable. This could be because intrastate crowdfunding investors may care about employment and growth at the state level and are not biased toward locals.

A potential concern is that the adoption of intrastate crowdfunding in a given state could be response to expectations of future economic growth in that state. If that were the case, a positive correlation between the adoption of intrastate crowdfunding and measures of entrepreneurship could not be interpreted as the causal effect of access to crowdfunding. I mitigate this concern in two ways. First, I examine the reasons mentioned by regulators for passing intrastate crowdfunding. I do not find any evidence that these regulations were a

[4]Michelacci and Silva (2007) argue that LBE is caused by the combination of two factors. Not only distance to financiers plays an important role in access to financing (Williamson, 1987; Petersen and Rajan, 2002; Berger et al., 2005) but also locals may have region specific collateral. For example financial intermediaries such as banks and VCs may have more information about locals or may believe that locals are less likely to engage in moral hazard because of local social pressure or peer effects (Arnott and Stiglitz, 1991).

response to observed or expected economic growth. In fact, many state regulators mention the decline in bank lending, venture capital investments, and small business activity after the 2008 financial crisis, and the delay in the passage of Regulation CF at the federal level as reasons for adopting intrastate crowdfunding. The passage of these regulations after the financial crisis thus seems to be the response of state-level regulators to a decrease in the supply of capital, rather than an increase in demand for capital.[5] Next, to alleviate the concern that intrastate crowdfunding was a response to economic growth (increase in demand for capital by entrepreneurs), I conduct tests of the parallel trend assumption and find no evidence of significant pre-trends in the outcome variables of interest.

After establishing that access to return-based crowdfunding encourages entrepreneurship, I examine whether it has a positive effect on the formation of successful businesses and real economic outcomes. In particular, the positive effect of intrastate crowdfunding and Regulation CF on the number of business applications suggests that entrepreneurs perceive access to crowdfunding to be helpful in establishing a business. However, it is not clear whether these businesses survive, turn into employer businesses, and/or have real economic effects. Interestingly, I find that intrastate crowdfunding and Regulation CF have distinguishably different effects on these factors.

First, although the positive effect of intrastate crowdfunding on the number of business applications (2%) is smaller than that of Regulation CF ($\approx$ 35%), it appears that only intrastate crowdfunding has a strong effect on the formation of employer businesses. In particular, I find that intrastate crowdfunding leads to a 2.8% (4.6%) increase in the number of business applications that turn into employer businesses one (two) year(s) after business applications are filed, especially in states with less developed financial markets. In contrast to intrastate crowdfunding, Regulation CF does not have any detectable effect on the formation of employer businesses one (two) year(s) after business applications are filed. There are several reasons that can explain why Regulation CF does not lead to employer business

[5] In addition, most of the intrastate crowdfunding laws are tied to the federal "intrastate offering exemption" and its Rule 147. Given that Rule 147 of the Securities Act was adopted in 1974, states had a lot of time to pass intrastate crowdfunding regulations in response to economic growth.

formation. First, businesses initiated after the passage of Regulation CF cannot raise capital through Regulation CF due to factors that negatively affect attracting investors, such as the low perceived quality of their business plans. Second, they fail after raising capital through Regulation CF because of the competition from other businesses or even competition from other entrants, or because of the quality of their business plans. Third, they raise capital through Regulation CF but they never had the intention or capacity to become employer businesses.

The third explanation is possible because I also observe that intrastate crowdfunding, but not Regulation CF, has positive and significant effects on the number of applications by businesses that pay or plan to pay wages to their employees[6] and on the number of business applications that are classified as having a high probability of becoming employer businesses.[7] One possible reason for these differences between intrastate crowdfunding and Regulation CF is relocation of entrepreneurs from states without intrastate crowdfunding laws to states that provide access to this method of financing. The financing limit under intrastate crowdfunding, in some states, is higher than the $1.075 million financing limit under Regulation CF over the sample period. This may encourage businesses with planned wages or with the goal to become employer businesses to move to states with intrastate crowdfunding or start their business in those states.[8]

Next, to investigate how impactful the passage of intrastate crowdfunding and Regulation CF are, I examine their effect on business dynamics and real economic outcomes. I find that intrastate CF has a 1.4% positive effect on job creation (excluding self-employment). It also

[6]The BFS dataset refers to these applications as "business applications with planned wages." More precisely, this is the subsample of business applications in the BFS dataset that indicate the first date that wages were or will be paid to employees. If the business does not plan to have employees, the applicant should enter "N/A," and the BFS dataset then does not classify this business as business applications with planned wages

[7]This subsample of business applications in the BFS dataset is called "high propensity business applications". High propensity business applications include applications by corporations, applications that indicate the business is hiring employees, applications with a first wages-paid date, and applications from industries such as manufacturing, retail, health care, etc.

[8]Given that the effect on the number of high propensity business applications is larger than the effect on the number of business applications with planned wages, many of these businesses should be active in industries categorized as high propensity industries by the Census.

increases self-employment by 0.14%, increases the number of non-employer establishments by 0.32%, and decreases job destruction by 4% to 5% in a state with an average pre-treatment level of bank deposits. However, I do not find any robust evidence that Regulation CF has a significant causal effect on these variables.

While intrastate crowdfunding improves job creation and self-employment, Regulation CF affects establishment entry and exit. In particular, my results suggest that Regulation CF helps small businesses survive longer but prevents other types of businesses from entering or expanding. This conclusion follows from two sets of results. First, in the entire sample, the passage of Regulation CF leads to a 14.5% (21%) decrease in establishment entry (exit). Second, focusing on small businesses (those with fewer than 20 employees), I find that Regulation CF does not have any significant effect on establishment entry by small businesses, but that it decreases establishment exits by these firms. In addition, I find evidence suggesting that more established firms are successful in using Regulation CF, while non-employer businesses that want to grow are not.

In summary, this paper shows that return-based crowdfunding regulations can decrease the importance of local financial market development in business initiation, mitigating the disparities in entrepreneurial activities across the U.S. states. However, it underscores that state-level (intrastate crowdfunding) and federal-level (Regulation CF) return-based crowdfunding regulations have significantly different effects on business formation, business dynamics, and real economic outcomes. Intrastate crowdfunding is more effective in helping businesses turn into employer businesses, increasing job creation, and decreasing job destruction. Instead, Regulation CF helps businesses that are already employer businesses to avoid shrinking their businesses and prevent other businesses from expansion or entry. A potential reason for these different effects is that the relatively larger geographical distance between business owners and investors in Regulation CF campaigns (compared to intrastate crowdfunding campaigns) exacerbates information asymmetry, and only the more established businesses can mitigate its negative effect on fundraising.[9]

[9]Consistent with this explanation, I observe that Regulation CF affects the business dynamics of firms that are active one to five years after becoming employer businesses rather than the business dynamics of

**Related Literature**

This paper contributes to the nascent literature on return-based crowdfunding. The theoretical papers in this area concentrate on three main topics: 1) determinants of entrepreneurs' decisions, such as choosing between reward-based crowdfunding (pre-ordering of product) and equity crowdfunding (Belleflamme et al., 2014) or determining the offering price in an equity crowdfunding campaign (Tzur and Segev, 2022); 2) the possibility of optimal allocation of capital through crowdfunding (Grüner and Siemroth, 2019);[10] and 3) optimal policies in crowdfunding offerings, such as optimal time-varying transparency policy (Glazer et al., 2021).

To the best of my knowledge, I am the first to empirically examine how access to return-based crowdfunding affects entrepreneurial activities and the importance of local financial market development in spurring these activities. In the empirical literature on equity crowdfunding, one of the main questions is whether or not equity crowdfunding attracts high-quality and innovative ventures. Catalini et al. (2016) conclude that Regulation CF may not provide high-growth start-ups with a viable source of financing. They argue that the high information asymmetry between entrepreneurs and investors in these financing campaigns may lead investors to discount the value of ventures or projects, deterring high-quality businesses from using Regulation CF to raise capital. Relatedly, Blaseg et al. (2021) investigate whether or not equity crowdfunding attracts low-quality entrepreneurs and show that entrepreneurs connected to distressed banks are more likely to use this source of financing.

The argument by Catalini et al. (2016) may provide a plausible explanation for my results that intrastate crowdfunding, but not Regulation Crowdfunding, spurs high propensity business applications and increases business formation. Information asymmetry may be lower in intrastate crowdfunding campaigns because within-state investors are typically better equipped to acquire information about the issuers.

firms that just became employer businesses. This observation suggests that more established firms may find raising capital through Regulation CF viable because their track record helps them mitigate information asymmetry concerns.

[10] In addition, there are theoretical papers, such as Strausz (2017) and Lee and Parlour (2022), that show crowdfunding from consumers can improve efficiency and welfare.

Another strand of empirical research on equity crowdfunding concentrates on factors and signals that determine the success of crowdfunding campaigns (Ahlers et al., 2015; Vismara, 2018; Ralcheva and Roosenboom, 2020; Donovan, 2021; Kleinert et al., 2022) and the effect of successful crowdfuding campaigns on future firm performance (Dolatabadi et al., 2021). Using a regression discontinuity design (RDD), Dolatabadi et al. (2021) show that a successful equity crowdfunding campaign has a positive effect on the future performance of the firm. They also provide suggestive evidence that firms that raise capital through Regulation CF are less likely than angel-backed firms to have subsequent funding rounds. This observation is in line with my findings that the passage of Regulation CF significantly increases the number of business applications but has no effect on business formation within two years after business applications are filed. Differently from Dolatabadi et al. (2021), I also explore the effect of intrastate crowdfunding and show that unlike Regulation CF, it has a positive effect on business formation and employment. My key contribution to both Dolatabadi et al. (2021) and other papers in this literature is to show that return-based crowdfunding decreases the role of local financial market development for entrepreneurship.

This paper also contributes to the literature on financial development, entrepreneurship, and growth. Several papers show that financial system development promotes economic growth at the country level (King and Levine, 1993a,b; Rajan and Zingales, 1998; Levine, 1997; Levine and Zervos, 1998) and particularly benefits small businesses (Beck et al., 2008). Other papers highlight the importance of local financial market development (Guiso et al., 2004) and the continued role of local branches (Nguyen, 2019) and branch networks (Gilje et al., 2016) on entrepreneurial activities and the supply of capital to small businesses. Improved local financial market development after the deregulation of the banking system spurs entrepreneurship and economic growth (Jayaratne and Strahan, 1996; Kerr and Nanda, 2009), decreases the size of the typical establishment because of the increased banking competition (Cetorelli and Strahan, 2006), decreases the cost of credit for small businesses (Rice and Strahan, 2010), and increases the total factor productivity (TFP) of small businesses (Krishnan et al., 2015). My paper shows that innovations in financing for start-ups and small businesses can decrease the importance of local financial market development and may decrease the disparities in entrepreneurial activities across states in the U.S.

My paper also contributes to the literature on the role of technological and financial innovations in access to financing and their effect on entrepreneurial activities. Barrios et al. (2020) show that access to gig economy platforms spurs entrepreneurial entry by providing a complementary source of income to entrepreneurs and a form of insurance against the risk of losing entrepreneurial income. Gopal and Schnabl (2022) show that FinTech lending to small businesses increased after the 2008 financial crisis and most of this increase substituted the decrease in bank lending after the crisis. In addition, Erel and Liebersohn (2020) show that FinTech lending expanded the supply of credit post COVID-19 rather than substituting PPP lending by banks. I find that both intrastate crowdfunding and Regulation CF increase the number of business applications by non-corporations, suggesting that return-based crowdfunding may play a complementary role to banks by attracting individuals and businesses that may have difficulty in accessing bank financing because they lack large assets or long track records. However, I also find that the passage of Regulation CF decreases establishment exits by small businesses, suggesting that this method of financing may be a viable alternative for bank lending after the 2008 financial crisis.

This paper is also related to the literature on the effects of the Jumpstart Our Business Startups (JOBS) Act. Dambra et al. (2015) and Lewis and White (2020) document an increase in the number of IPOs, proceeds of IPOs, and employment by emerging growth companies (EGCs) after Title I of the JOBS Act. Other papers that investigate the effect of Title I of the JOBS ACT on the IPO market and behavior of market participants are Barth et al. (2017), Chaplinsky et al. (2017), and Agarwal et al. (2022). Chu et al. (2022) show that after Title I of the JOBS Act the abnormal cumulative return of acquirers in acquisitions of private targets decreased. Gupta and Israelsen (2014) show that lower disclosure requirements under Title I of the JOBS Act increases IPO underpricing and post-IPO illiquidity. My paper provides evidence on the effects of Regulation CF (Title III of the JOBS Act) on entrepreneurial activities, business formation, and real economic outcomes.

## 1.2 Institutional Details

Under the Securities Act of 1933 in the U.S., all issuers must register securities with the Securities and Exchange Commission (SEC) unless an exemption is available. A registered offering may take up to six months or longer and can cost over 10% of the offering amount (U.S. Government Accountability Office, 2000; Cohn and Yadley, 2007). The cost of a registered offering may not be manageable for small firms.[11] In order to facilitate capital formation for small businesses, federal and state securities regulators provide several exemptions from the securities registration. These exemptions are provided by Regulation D, Regulation A, Regulation CF, and intrastate crowdfunding.

Regulation A and Regulation D provide exemption from registration with the SEC. While there is no limit on the financing amount under Regulation D, an issuer can sell securities only to accredited investors. Under Regulation A, issuers had to get approved for blue sky laws in all states they wanted to raise capital in, a requirement of Regulation A that is lifted under Regulation A+ (Title IV of the JOBS Act). While Regulation A+ allows issuers to raise capital from both accredited and non-accredited investors in the form of debt or equity, the financing amount is limited to $50 million per year.[12] In contrast to Regulation D, Regulation CF and intrastate crowdfundig allow issuers to raise capital from both accredited and non-accredited investors. Although the financing limit under Regulation CF and in many states under intrastate crowdfunding is lower than the financing limit under Regulation A+, the disclosure requirements for Regulation CF and intrastate crowdfunding are less restrictive. As a result, Regulation CF and intrastate crowdfunding can be used at earlier stages of financing.

**1. Regulation Crowdfunding (CF).** Under Regulation CF, issuers are exempted from registration with the SEC and from complying with state-level blue sky laws, and can offer and sell securities nationwide. Regulation CF, Title III of the JOBS Act, went into effect

[11] The results of analysis of IPO offerings by the U.S. Government Accountability Office indicate that "the average total cost to conduct a small business IPO during 1994-99 was about 10 percent of total offering proceeds, while the average total cost for a large business IPO was about 8 percent." (U.S. Government Accountability Office, 2000)

[12] The financing limit was raised to $75 million in 2020.

on May 16, 2016 and allows startups to raise upto \$1.07 million[13] from both accredited and non-accredited investors. According to SEC guidelines for Regulation CF, there is no limit on the number of investors, and the amounts that individual investors are allowed to invest in all Regulation CF offerings over a 12-month period are determined based on investor's annual income or net worth.

**2. Intrastate Crowdfunding.** This regulation allows businesses to raise capital from both accredited and non-accredited in-state investors. Thirty-four states and the District of Columbia provide firms with exemption from state level registration through intrastate crowdfunding laws. Table 1.1 provides information on the intrastate crowdfunding laws in these 34 states and District of Columbia.

**[See Table 1.1]**

Most of the intrastate crowdfunding laws are tied to the federal "intrastate offering exemption," Section 3(a)(11) of the Securities Act of 1933 ("Securities Act") and its Rule 147. A few of them are tied to the federal exemption in Rule 504 of Regulation D. Rule 147, which is a "safe harbor" under Section 3(a)(11), provides the requirements that issuers should meet in order to use the "intrastate offering exemption." According to the Rule 147, [14] the issuer must be organized and have its principal place of business[15] in the state where it offers and sells securities. The issuer can offer and sell securities only to in-state residents and it is the responsibilty of the firm to detemine the residence of each offeree and purchaser. In 2016, the SEC established Rule 147a as an amendment to Rule 147. Rule 147a allows firms to offer securities to out-of-state residents as long as the sales are only made to in-state residents. Also a firm can use intrastate crowdfunding even if it is incorporated or organized out-of-state as long as its principal place of business is in-state.

**Comparison between Regulation CF and Intrastate Crowdfunding.** While Regulation CF allows issuers to sell securities nationwide and raise more awareness about their

[13]The financing limit was raised to \$5 million in 2020.
[14]See https://www.ecfr.gov/current/title-17/chapter-II/part-230#230.147.
[15]The firm should satisfy at least one "doing business" requirement mentioned in Rule 147.

businesses, intrastate crowdfunding rules may allow higher financing limits, require less-stringent filing requirements, and allow higher investment limits by accredited and non-accredited investors.

## 1.3 Data

### 1.3.1 Outcomes

I use the Business Formation Statistics (BFS) provided by the U.S. Census Bureau. This dataset provides information on new business applications and formations in the U.S., and can be used to study business initiation activity and realized business formation.

The BFS dataset includes information from applications for an Employer Identification Number (EIN)[16] through the IRS Form SS-4.[17] On this form, an applicant includes information on the state and county of the principal place of business, the type of entity,[18] and whether or not the reason for application is starting a new business.

The BFS dataset provides information on four different subsets of the applications for EINs. I use these four data series at the state level from 2009 to 2019. The data after 2019 are not included in the analysis so that the results are not affected by outcomes from the COVID-19 pandemic. These four data series are explained below and Figure 1.1 illustrates the relationship between these series.

**[See Figure 1.1]**

- Business Applications (BAs): This series provides the number of applications for EINs.

- High-propensity Business Applications (HBAs): This series provides the number of

[16]EINs are IDs used by business entities for tax purposes. Business owners need EINs to open business bank accounts, apply for business licenses, and for tax purposes. Any employer business (including sole proprietors) needs an EIN. A non-employer business that operates as a corporation, a partnership, or a multi-member LLC is required to have an EIN. Self-employers that have Keogh plans or solo 401(k) retirement plans must have EINs. Also, some self-employers get EINs to avoid using their SSN and prevent identity theft.

[17]This form can be find here: https://www.irs.gov/forms-pubs/about-form-ss-4

[18]Among possible options, I can mention limited liability company (LLC), sole proprietorship, partnership, corporation, nonprofit organization, etc.

business applications that have a high propensity of turning into businesses with payroll.[19]

- Business Applications with Planned Wages (WBAs): This series provides the number of HBAs that indicate a planned date to pay wages or a first wages-paid date on IRS Form SS-4.

- Business Applications from Corporations (CBAs): This series provides the number of HBAs by entities marked as a corporation or personal service corporation on IRS Form SS-4.

The BFS dataset also provides data on business formation, i.e. the number of business applications that turn into employer businesses within one(two) year(s) after business applications are filed. In order to identify employer business formation, the Census uses the first instance of payroll tax liabilities on the business applications. The data on business formation within one(two) year(s) after business applications are filed is available until the end of 2018 (2017).

I also use the Business Dynamics Statistics (BDS) database provided by the U.S. Census Bureau. This database tracks establishments' job flow,[20] entry, and exit for the whole economy or by firm or establishment characteristics. I use the data on job creation and destruction, and establishment entry and exit for the whole sample and by firm age and size. I consider firms with fewer than 20 employees as small businesses. I also use firm age data to investigate whether return-based crowdfunding methods mostly help non-employer businesses that want to grow or businesses that are already employer businesses.

To investigate the effect of access to crowdfunding on non-employer and small employer

[19] The Census website states that "The identification of high-propensity applications is based on the characteristics of applications revealed on the IRS Form SS-4 that are associated with a high rate of business formation. High-propensity applications include applications: (a) for a corporate entity, (b) that indicate they are hiring employees, (c) that provide a first wages-paid date (planned wages); or (d) that have a NAICS industry code in accommodation and food services (72) or in portions of construction (237, 238), manufacturing (312, 321, 322, 332), retail (44, 452), professional, scientific, and technical services (5411, 5413), educational services (6111), and health care (621, 623)."

[20] This database excludes self-employment, as well as proprietors and partners of unincorporated businesses.

businesses, I use the Nonemployer Statistics (NES) dataset, County Business Pattern (CBP) dataset, and non-farm proprietors' employment data from 2009 to 2019.

The NES provide the number of and total receipts by businesses that have no paid employees and are subject to federal income tax. Studying this group of businesses is important because based on the Census information, 72.6% of establishments in the U.S. in 2016 were nonemployers or businesses with no paid employees.[21]

However, in order to get a complete picture of businesses in the U.S., I use the County Business Pattern (CBP) dataset provided by the U.S. Census Bureau, which includes the following data points on businesses with paid employees: the number of establishments, employment during the week of March 12, and annual payroll. Given that these data points are provided for all employee size classes, I can concentrate on small businesses. In addition, non-farm proprietors' employment data is provided by the Bureau of Economic Analysis (BEA), and includes the number of non-farm sole proprietorships and the number of individual general partners in non-farm partnerships.[22]

I use the American Community Survey (ACS) data from 2009 to 2019 provided by the U.S. Census to test the effect of access to return-based crowdfunding on local bias in entrepreneurship. These data provide information on an individual's place of birth, place of work, age, sex, education, marital status, race, and whether or not they are self-employed. If an individual is self-employed, it is determined whether the business is incorporated or not. Following Michelacci and Silva (2007), I consider individuals as locals if they are working in the states where they were born. This dataset allows me to test whether the relation between being a local and self-employment changes after the passage of crowdfunding regulations.

### 1.3.2 Measures of Local Financial Market Development

Some measures of financial market development (depth) proposed in previous studies are scaled measures of credit issued to non financial private firms (King and Levine, 1993a) or

[21] See https://www.census.gov/library/stories/2018/09/three-fourths-nations-businesses-do-not-have-paid-employees.html.

[22] See https://www.bea.gov/system/files/methodologies/LAPI-Methodology.pdf for a detailed explanation on how these numbers are calculated.

bank deposits (Kerr and Nanda, 2011).

In order to define measures of local financial market development (depth) based on the supply of capital to the private sector (small businesses), I use the Community Reinvestment Act (CRA) data published by the Federal Financial Institutions Examination Council (FFIEC). Under the CRA, all insured depository institutions with assets greater than $1 billion[23] must disclose annual data on the number and dollar volume of loans with origination amounts less than or equal to $1 million and on the number and dollar volume of loans originated to businesses with gross annual revenues less than or equal to $1 million. These data are reported based on the location of the borrower, not the location of the bank. Although the CRA data only covers small business lending by banks with total assets above a certain threshold, these depository institutions account for 86% of total small business lending (Greenstone et al., 2020).

I also measure local financial market development using bank deposit data at the state level. I use the summary of deposits data provided by the Federal Deposit Insurance Corporation (FDIC). This database provides the amount of branch deposits as of June 30 of each year.

### 1.4 Methodology

To test the effect of access to crowdfunding on dependent variables of interest, I use two empirical settings: 1) staggered adoption of intrastate crowdfunding by 34 states and the District of Columbia; and 2) the passage of Regulation CF in 2016.

Studying the effect of access to crowdfunding on entrepreneurial activities and real economic outcomes by running a naive regression of an outcome variable of interest on the amount of capital raised through crowdfunding faces several obstacles. States that tap more into crowdfunding to raise capital may differ on unobservable time-variable dimensions from states that use crowdfunding less. As a result, comparing measures of entrepreneurial activities between states that use crowdfunding more and states that use it less may capture the

[23] The exact threshold for each year can found at: https://www.ffiec.gov/cra/reporter.htm .

effect of these unobservable factors. For example, entrepreneurs may relocate to a certain state for unobservable reasons and use crowdfunding to finance their ventures. Running a naive regression in this case overestimates the effect of access to crowdfunding on measures of entrepreneurial activities.

Also, the changes in the amount of capital raised through crowdfunding can be driven or accompanied by unobservable factors, such as unobservable economic growth that at the same time affects the dependent variable of interest. If states experience unobservable economic growth after the passage of intrastate crowdfunding, the naive regression will overestimate the effect of access to crowdfunding on measures of entrepreneurial activities.

In the following subsections, I will explain how each of the empirical settings considered in this paper can address these issues, what are possible concerns in each setting, and how these concerns can be alleviated. I also explain the estimation strategies used in each setting.

### 1.4.1 Intrastate Crowdfunding

I employ a staggered differences-in-differences (DiD) design to examine the staggered adoption of intrastate crowdfunding by 35 states/territories in the U.S. over the period of 2009 to 2019. One advantage of the staggered adoption of these regulations is that at each point in time there is a control group that helps to control for aggregate changes in the economy that affect both the treatment and control groups. The parallel trend assumption makes controlling for changing economic conditions possible. If the parallel trend assumption holds, it means that changes in the outcome variable over time would have been exactly the same in both the treatment and control groups in the absence of the intervention. Another advantage of a staggered DiD approach over a simple DiD approach is that it is harder to claim that an event occurred at the passage of each regulation and drove the changes in the dependent variables.

However, the passage of these regulations mitigates endogeneity concerns to the extent that states did not pass them in response to demand by entrepreneurs or in expectation of changing economic climate. As a result, the political economy of these state-level laws becomes important.

Gathering information on the reasons mentioned for the passage of intrastate crowdfunding laws, I find that the intrastate crowdfunding laws were passed as a response to the 2008 financial crisis. The 2008 financial crisis decreased bank lending and venture capital investments, leading to a decrease in small businesses' activities. The Jumpstart Our Business Startups (JOBS) Act was an effort to increase entrepreneurs' and businesses' access to capital after the 2008 financial crisis. However, the delay in the passage of title III of the JOBS Act (Regulation CF) made many states pass intrastate crowdfunding laws. I do not find evidence that these laws were passed in expectation of changing economic climate at the state level; they were passed in response to capital supply shock, to provide an alternative to Regulation CF with less stringent compliance and disclosure requirements, or to encourage entrepreneurial activities and increase employment at the state level.

Another argument to support the claim that intrastate crowdfunding regulations were a response to the consequences of the 2008 capital supply shock is as follows: Most of the intrastate crowdfunding laws are tied to the federal "intrastate offering exemption," Section 3(a)(11) of the Securities Act and its Rule 147. Rule 147 was adopted in 1974. As a result, it is not clear why states had to wait until after the 2008 financial crisis if they wanted to pass intrastate crowdfunding laws in response to increased demand for capital by entrepreneurs or in response to expected economic growth.

Another concern about endogeneity of passage of intrastate crowdfunding laws may be that states that were more seriously affected by the 2008 financial crisis may be more likely to pass intrastate crowdfunding regulations. However, the economic activity in those states should be more negatively affected by the financial crisis and this bias would work against finding a positive effect of access to crowdfunding on the measures of entrepreneurship. As a result, the positive effects found through regression specifications in this paper are likely to be lower bounds for the effect of access to crowdfunding on entrepreneurial activities.

**Estimation Strategies**

To study the effect of intrastate crowdfunding on outcome variables, I employ two regression specifications: 1) staggered DiD and 2) staggered DiD with continuous treatment, where the treatment intensity is a measure of local financial market development before treatment.

**Staggered Differences-in-Differences.** The staggered DiD specification in equation 1.1 allows me to estimate the average effect of intrastate crowdfunding laws on dependent variables. The outcome variables of interest are: 1) the number of business applications from the BFS dataset; 2) the number of business applications that turn into employer businesses one (two) year(s) after the applications are filed (BFS dataset); 3) the number of and total receipts by nonemployer businesses from the NES dataset; 4) employment by non-farm proprietors provided by the BEA; 5) the number of establishments, employment during the week of March 12, and annual payroll by employer businesses from the CBP dataset; and 6) job creation and destruction, and establishment entry and exit from the BDS dataset.

$$Ln(Y_{st}) = \beta * D_{st} + \tau_t + \pi_s + \epsilon_{st}, \tag{1.1}$$

In equation (1.1), $Ln(Y_{st})$ denotes the logarithmic transform of a dependent variable in state $s$ at time $t$. $D_{st}$ denotes a dummy variable that takes a value of 1 if state $s$ has intrastate crowdfunding regulations at time $t$, otherwise, it is equal to zero. $\tau_t$ and $\tau_s$ denote respectively, time fixed effects and state fixed effects. Given that the outcome variables can be serially correlated at the state level, standard errors are clustered at the state level. In equation (1.1), the coefficient of interest is $\beta$, which shows on average how many percentage points an outcome variable changes in a state when an intrastate crowdfunding law is passed.

First, I consider equation (1.1) and test the parallel trend assumption without including any controls in the regression. If the parallel trend assumption can not be rejected even without conditioning on control variables, I can more strongly argue that the passage of intrastate crowdfunding laws were exogenous to the state-level conditions. Then I add controls for the percentage change in population ($Ln(Pop_{st})$) and the percentage change in GDP ($Ln(GDP_{st})$). Given that I am using a staggered DiD design, the specification in equation

(1.1) is accurate as long as there is no abnormal change in the population or GDP growth rate of a treated or non-treated state over time.

**Staggered Diferences-in-Differences with Continuous Treatment.** Equation (1.2) presents the baseline specification for the case of staggered DiD with continuous treatment. As in equation (1.1), the control variables are not included for similar reasons. Later they are added to equation (1.2) to capture heterogeneity among states that may affect outcome variables.

$$Ln(Y_{st}) = \beta * D_{st} + \zeta * Ln(Measure_{s,pretreatment}) * D_{st} + \tau_t + \pi_s + \epsilon_{st} \tag{1.2}$$

$Measure_{s,pretreatment}$ is a measure of local financial market development (depth) in the year before the adoption of an intrastate crowdfunding law by state $s$. I consider the following measures of local financial market development: pre-treatment level of bank deposits, pre-treatment number of loans to small businesses, and pre-treatment amount of loans to small businesses. I have access to the data on two types of small business loans: 1) loans with origination amounts below $1M; and 2) loans to businesses with revenue below $1M. As a result, I consider five measures of local financial market development.

Equation (1.2) allows me to estimate the differential effect of passage of intrastate crowdfunding on the dependent variable ($Y_{st}$) depending on the pre-treatment level of local financial market development. If access to return-based crowdfunding is less important to entrepreneurs in more financially developed states, then the coefficient $\zeta$ should be significant and negative. Note that the coefficient $\beta$ alone is not informative in this setting. But, if $\beta + \zeta * Ln(Measure_{s,pretreatment})$ for the average pre-treatment level of local financial market development is positive, then on average the passage of intrastate crowdfunding spurs entrepreneurial activities or improves real economic outcomes at the state level.

**Testing the parallel trend assumption.** The parallel trend assumption is a key identifying assumption in the staggered DiD design. Although it is not possible to prove in any DiD approach that the parallel trend assumption holds, I estimate the dynamic versions of equations (1.1) and (1.2) with/without controlling for $Ln(Pop_{s,t})$ and $Ln(GDP_{s,t})$ to show that the parallel trend assumption cannot be rejected. I also use the method proposed by Sun and Abraham (2021) to make sure that the parallel trend assumption cannot be rejected even after using their recently proposed estimator.

### 1.4.2 Regulation CF

I use the passage of Regulation CF at the federal level in 2016 in a DiD empirical design with continuous treatment. The treatment intensity is a measure of local financial market development (depth) before treatment. Access to financing through crowdfunding should be more important in states with lower levels of financial development.

Given that Regulation CF is a federal regulation, it shouldn't be correlated with changing local economic situations at the state level. In addition, one key assumption for identification of treatment effect is that there was no other change in 2016 that affected the dependent variables across the states in precisely the same way as Regulation CF affected them through local financial market development.

The parallel trend assumption in this case is that an outcome variable in states with different levels of local financial market development would have changed in the same way if Regulation CF had not been passed. If the parallel trend assumption holds, then states with different levels of local financial market development would play the role of control group for each other to help control for changes in economic conditions that affect states with different levels of local financial market development.

To estimate the effect of Regulation CF on measures of entrepreneurship or real economic outcomes, I use a regression specification similar to equation (1.2) with the exception that $D_{st}$ is a dummy variable that takes a value of 1 for all states from 2016 onward. Also, treatment intensity ($Ln(Measure_{s,pretreatment})$) is the level of local financial market development at the state level in 2015. I use a dynamic version of equation (1.2) to test the parallel trend assumption. For the reasons mentioned above, I first test the parallel trend assumption without considering any control variables and then step by step I add control variables for population growth ($Ln(Pop_{st})$) and GDP growth ($Ln(GDP_{st})$).

### 1.4.3 Local Bias in Entrepreneurship

I use equations (1.3) and (1.4) to test whether access to intrastate crowdfunding changes the level of local bias in entrepreneurship documented by Michelacci and Silva (2007).

$$Local_{ist} = \lambda * En_{ist} + \alpha * D_{st} + \beta * En_{ist} * D_{st} + \delta . X_i + \tau_t + \pi_s + \epsilon_{ist}, \tag{1.3}$$

$$\begin{aligned} Local_{ist} = \lambda * En_{ist} + \alpha * D_{st} + \beta * En_{ist} * D_{st} + \zeta * En_{ist} * Ln(Measure_{pretreatment}) + \\ \rho * Ln(Measure_{pretreatment}) * D_{st} + \gamma * En_{ist} * Ln(Measure_{pretreatment}) * D_{st} + \\ \delta * X_i + \tau_t + \pi_s + \epsilon_{ist}, \end{aligned} \tag{1.4}$$

Where $Local_{ist}$ denotes a dummy variable that is set equal to one if, in year ($t$), the head of household ($i$) works in the state ($s$) that he (she) was born in. $En_{ist}$ is a dummy variable that is set equal to one if the head of household ($i$) is self-employed in state ($s$) and year ($t$) independent of whether the business is incorporated or unincorporated. $X_i$ denotes the set of individual level control variables, such as age, sex, marital status, number of children, dummies for race, and dummies for educational achievements. In both equations (1.3) and (1.4), $D_{st}$ is a dummy variable that is equal to 1 if state $s$ has intrastate crowdfunding laws in year $t$. $Measure_{s,pretreatment}$ is a measure of the pre-treatment level of local financial market development as defined in the previous subsection.

In equation (1.3), where I use a staggered DiD design, the coefficient $\lambda$ estimates the magnitude of local bias in entrepreneurship before the passage of intrastate crowdfunding. If $\lambda$ is positive and significant, it means that individuals who work in the states they were born are more likely to be self-employed (i.e. there is local bias in entrepreneurship). The coefficient $\alpha$ measures the changes in the probability that individuals in state $s$ work in that state after the passage of intrastate crowdfunding. $\beta$ is the coefficient of interest in equation (1.3) and it shows whether the magnitude of local bias in entrepreneurship changes after the passage of intrastate crowdfunding laws.

In equation (1.4), I use a triple DiD design to estimate whether there is a differential effect of access to intrastate crowdfunding on local bias in entrepreneurship depending on the pre-treatment level of local financial market development. The coefficient $\gamma$ in equation (1.4) measures this differential effect. Michelacci and Silva (2007) show that LBE is more present in states with a high level of local financial market development.[24] A negative and significant value for coefficient $\gamma$ implies that access to intrastate crowdfunding encourages non-locals to become self-employed more in states with higher levels of local financial market development.

Next, to test the effect of Regulation CF on local bias in entrepreneurship, I use regression specifications similar to equations (1.3) and (1.4) with the exception that $D_{st}$ is a dummy variable that takes value of 1 for all states from 2016 onward. The definition of other variables and coefficients are similar to what is mentioned above.

### 1.5 Results

In this section, I document the effect of access to return-based crowdfunding on the total number of business applications. Then, to understand what type of businesses or who benefits most from decreased frictions in access to financing, I study sub-samples of business applications and sub-samples of entrepreneurs based on where they were born. Finally, I investigate the effect of these regulations on business formation and real economic outcomes to assess the effectiveness of these regulations and the quality of businesses that are spurred by them.

#### 1.5.1 Business Applications

I do not find any significant effect of intrastate crowdfunding on the total number of business applications in equation (1.1). However, this result masks an important heterogeneity across states. Conditioning on the pre-treatment level of local financial market development (depth) in regression equation (1.2), I find that intrastate crowdfunding has a positive and significant

[24]One reason might be that locals have better connections to access local sources of financing.

effect on the total number of business applications and that this effect is larger in states with less developed local financial markets. Table 1.2 shows the regression results for two measures of local financial market development: the total amount of loans with origination amounts less than or equal to $1 million and the level of bank deposits. Tables OA-1 and OA-2 in the Online Appendix [25] show that this observation is robust to using other measures of local financial market development (depth) defined based on the supply of capital to small businesses.

**[See Table 1.2]**

Figures (1.2) to (1.4) show that the parallel trend assumption cannot be rejected when local financial market development is measured by the amount of loans with origination amounts less than or equal to $ 1 million (columns (1) to (3) in Table 1.2). These figures show the coefficient on the interaction between the pre-treatment level of local financial market development and the dummy for the passage of intrastate crowdfunding. This coefficient is close to zero and insignificant in the years before the adoption of intrastate crowdfunding laws. However, there is a sudden drop in the coefficient after the passage of intrastate crowdfunding, showing that the passage of these laws has a smaller effect on the number of business applications in states with higher pre-treatment levels of local financial market development. Figures OA-1 to OA-12 in the Online Appendix show similar results when other measures of local financial market development are used.

**[See Figure 1.2]**

**[See Figure 1.3]**

**[See Figure 1.4]**

Table 1.2 also shows that the average effect and the differential effect of intrastate crowdfunding on the total number of business applications depending on the pre-treatment level of

[25] The online appendix is available at https://www.hediehrashidi.com/research

local financial market development are economically significant. For example, in column (2) of Table 1.2, the average treatment effect on the treated states is 1%.[26] The total number of business applications in a state with an average level of pre-treatment amount of loans with origination amounts less than or equal to \$1 million increases by 326 in one year. In addition, a 10% decrease in the pre-treatment amount of such loans increases the effect of access to intrastate crowdfunding on the total number of business applications by 0.68%. Table 1.3 similarly shows that the passage of Regulation CF has a positive effect on the number of business applications, and that this effect is stronger in states with a lower pre-treatment amount of loans with origination amounts below \$1 million or with lower pre-treatment levels of bank deposits. Tables OA-3 and OA-4 in the Online Appendix show that this result is robust to considering other measures of local financial market development.

**[See Table 1.3]**

Tests of the parallel trend assumption for specifications (1) to (3) in Table 1.3 are presented in Figures 1.5 to 1.7. The coefficients on the interaction between the pre-treatment measure of local financial market development and the dummies for time relative to the passage of Regulation CF are presented in these figures. These coefficients are not statistically significant at the 5% level in any of the pre-treatment periods. As a result, the parallel trend assumption cannot be rejected. Figures OA-13 to OA-24 in the Online Appendix show that the parallel trend assumption holds for all measures of local financial market development when I do not include any control variable in the regressions or if I only control for $Ln(Pop_{s,t})$. However, controlling for both $Ln(Pop_{s,t})$ and $Ln(GDP_{s,t})$ makes the coefficient on the interaction term significant at the 5% level in one pre-treatment period when the measure of local financial market development is the number of loans with origination amounts below \$1 million or the amount of loans to businesses with revenue less than or equal to \$1 million.

[26]In specification (2) of Table OA-1 in the Online Appendix, where the measure of local financial market depth is the amount of loans to businesses with less than \$1 million in revenue, the average treatment effect on the treated states is 2%. A 10% decrease in the pre-treatment amount of such loans increases the effect of access to intrastate crowdfunding on the total number of business applications by 0.62%

**[See Figure 1.5]**

**[See Figure 1.6]**

**[See Figure 1.7]**

The results in column (2) of Table 1.3 show that, in a state with an average pre-treatment amount of loans with origination amounts less than or equal to $1 million, the number of business applications increases by 36.8% (≈12,000 business applications) after the passage of Regulation CF. A 10% decrease in the amount of these loans increases the positive effect of Regulation CF by 0.44%.[27]

### 1.5.2 Subsamples of Business Applications

It is important to understand what type of entrepreneurial activities are spurred by return-based crowdfunding and what type of organizations use this method of financing. Answers to these questions clarify how impactful this method of financing is and what type of businesses benefit most from decreasing frictions in access to financing.

The results in tables 1.4 and 1.5 show that intrastate crowdfunding and Regulation CF have a positive effect on the number of business applications by non-corporations, such as sole proprietorships, LLPs, and LLCs.[28] This positive effect is stronger in states with lower pre-treatment levels of local financial market development. For example, the results in column (2) of Table 1.4 and column (2) of Table 1.5 show that the passage of intrastate crowdfunding and Regulation CF, on average, increase the number of business applications by non-corporations by 0.39% (≈ 107) and 49.8% (≈ 13,717). In addition, with a 10% decrease in the pre-treatment level of the amount of loans with origination amounts below $1

[27]If the amount of loans to businesses with less than $1 million in revenue is used as the measure of local financial market development, then the number of business applications increases by 35.7% after the passage of Regulation CF. A 10% decrease in the amount of these loans increases the positive effect of Regulation CF by 0.4% (specification (2) of Table OA-3 in the Online Appendix).

[28]According to Form SS-4 instructions, by default, a domestic LLC with only one member is disregarded as an entity separate from its owner and the owner should choose "Other" as the type of entity. Also a domestic LLC with two or more members is treated as a partnership. However, a domestic LLC can avoid either default classification by filing Form 8832 to elect to be classified as a corporation for tax purposes.

million, the positive effect of intrastate crowdfunding on the number of business applications by non-corporations increases by 0.64% (≈ 176) and 0.48% (≈ 132). Figures OA-25 to OA-30 in the Online Appendix show that the parallel trend assumption cannot be rejected for any of the specifications in Table 1.4. Figures OA-31 to OA-36 in the Online Appendix lead to a similar conclusion regarding specifications in Table 1.5. I also find that intrastate crowdfunding does not have a significant effect on the number of business applications by corporations. Table table OA-5 in the Online Appendix shows that Regulation CF exerts a weak effect on the number of business applications by corporations, which is not robust to using different measures of local financial market development. In summary, both methods of return-based crowdfunding have a strong effect on the number of business applications by non-corporations. This observation shows that frictions in access to financing have mainly prevented the market entry of individuals and small entities.

**[See Table 1.4]**

**[See Table 1.5]**

There are possible scenarios on how return-based crowdfunding may mitigate the frictions in access to financing for non-corporations. It is possible that the market power of banks in some locations leads to high interest rates on loans offered to these small entities, making it nearly impossible for them to borrow money. However, return-based crowdfunding may compete with banks in supply of capital and incentivizes them to offer lower rates to small entities.

Also, these small entities may not have the collateral necessary to borrow money from banks[29] or long enough track record[30] to convince banks or other sophisticated investors

[29]An excerpt from a public comment about Regulation CF on the SEC website: "I believe - through my own many-fold experiences in the U.S.A as an immigrated minority with zero personal Credit-score nor local so-called "networking", that crowdfunding, the system of collaborative or shared financing, can not only help close the gap between entrepreneurs who desperately need equity capital to start or expand their businesses and too big to fail Corporations." Please refer to https://www.sec.gov/comments/jobs-title-iii/jobstitleiii-254.htm.

[30]An excerpt from a public comment about Regulation CF on the SEC website: "VCs, super angels and angel groups have all migrated to later stage investments often demanding companies already have substantial revenues before they will invest." Please refer to https://www.sec.gov/comments/jobs-title-ii/jobstitleii-91.pdf.

about the quality of their businesses. As a result, competition from larger businesses to raise capital may prevent banks or other sophisticated investors from investing in these small entities. However, return-based crowdfunding provides a new source of financing and investors in return-based crowdfunding campaigns may not have access to the same investment opportunity sets as those of banks or venture capitalists (VCs) and may be more willing to invest in younger and more risky projects. Risk sharing among return-based crowdfunding investors by investing small amounts in these projects may increase the possibility that they invest in these projects. In addition, many crowdfunding investors are not sophisticated and may not evaluate projects as accurately as banks or other sophisticated investors.

The results in table 1.6 show that the passage of intrastate crowdfunding has a positive and significant effect on the number of business applications with planned wages and on the number of high-propensity business applications. The results also show that this method of financing is more effective in states with lower levels of local financial market development. The results in columns (3) and (6) show that the passage of intrastate crowdfunding, on average, increases the number of business applications with planned wages by 0.8% ($\approx 49$) and the number of high-propensity business applications by 2.55% ($\approx 353$). Also, with a 10% decrease in the amount of loans with an origination amount below $1 million, the positive effect of intrastate crowdfunding on the number of business applications with planned wages increases by 0.38% ($\approx 23$) and on the number of high-propensity business applications increases by 0.34% ($\approx 47$). I do not find that Regulation CF has a significant effect on these types of business applications. Figures OA-37 to OA-42 in the Online Appendix show that the parallel trend assumption cannot be rejected in any of the specifications in Table 1.6.

**[See Table 1.6]**

It appears that intrastate crowdfunding has a higher chance of affecting real economic outcomes such as employment. Businesses with planned wages may use intrastate crowdfunding instead of Regulation CF because raising capital through intrastate crowdfunding is cheaper due to less stringent requirements[31] and in the period I consider, several states

[31] An excerpt from an article on why intrastate crowdfunding is beating Regulation CF: “Intrastate based

have financing limits above the $1.07 million financing limit under Regulation CF. Also, intrastate crowdfunding campaigns focus more on employment and economic growth at the state level. Figures OA-155 and OA-156 in the Online Appendix present quotes from two companies that used intrastate crowdfunding in Michigan. However, it is also possible that businesses with high propensity to become employer businesses relocate to states with intrastate crowdfunding, increasing the number of business applications with planned wages or with high propensity in these states. Given that Regulation CF was adopted at the federal level businesses do not need to relocate to use this method of financing.[32]

### 1.5.3 Local Bias in Entrepreneurship

Table OA-6 in the Online Appendix reports the results from running the main regression specification in Michelacci and Silva (2007) using the American Community Survey samples from 2009 to 2019. In contrast to Michelacci and Silva (2007), I do not find a significant relation between being a local and an entrepreneur in the sample that includes all races. However, for the sample of white and black individuals, I observe significant local bias in entrepreneurship. The magnitude of local bias in entrepreneurship is larger for white individuals, showing that white individuals can better exploit local financing sources than local black individuals. In general, the significance and magnitude of local bias in entrepreneurship is lower in my sample than in the U.S. Census 2000 1% file data used by Michelacci and Silva (2007), suggesting that local bias in entrepreneurship has decreased overtime.

The results from the DiD regression in equation (1.3) are not significant in both cases of intrastate crowdfunding and Regulation CF. However, the results in Tables 1.7 and **??** show

investment crowdfunding today is superior to the interstate Regulation Crowdfunding aka REG-CF option representing lower friction, a lower cost of capital and access to larger investment amounts from everyday people." Please see https://www.crowdfundinsider.com/2019/02/144160-the-state-of-investment-crowdfunding-how-intrastate-crowdfunding-is-beating-reg-cf-on-the-cost-of-capital-and-how-to-fix-it/.

[32] "Georgia is one of the leaders in this area. The Invest Georgia Exemption ("IGE") provides a broad crowdfunding exemption that allows issuers to raise amounts up to $5 million (with integration of all investment funds received in the previous twelve months). This is the largest cap of any of the various state crowdfunding exemptions and has been a major benefit to local companies raising equity funds. It has also helped attract companies from out of state to relocate to Georgia." Quoted from https://www.techfundingandlegal.com/securities-law/state-crowdfunding-and-the-invest-georgia-exemption/.

that conditioning on measures of local financial market development in the triple DiD regression in equation (1.4) leads to a negative and significant effect of intrastate crowdfunding on the local bias in entrepreneurship independent of the pre-treatment level of local financial market development.[33] After the passage of intrastate crowdfunding, the probability that an entrepreneur is located in the state where they were born decreases by 0.007. Moving from the sample that includes all races to the sample that includes only white individuals, this probability decreases by 0.008. This result shows that investors in intrastate crowdfunding campaigns are willing to finance viable start-ups founded by non-local entrepreneurs. This may be because issuers that use intrastate crowdfunding should operate mainly in the state in which they raise capital, helping to increase employment in that state. However, the results in Tables OA-8 and OA-9 show that the passage of Regulation CF does not have a significant effect on the local bias in entrepreneurship. This might be because many states passed intrastate crowdfunding before the passage of Regulation CF.

**[See Table 1.7]**

### 1.5.4 Business Formation

I next study the effect of access to intrastate crowdfunding and Regulation CF on the number of business applications that lead to employer businesses in one (two) year(s) after business applications are filed. Running the DiD regression in equation (1.1), I do not find significant effects of intrastate crowdfunding and Regulation CF on these measures of employer business formation. However, results from DiD regressions with continuous treatment (equation (1.2)) show that intrastate crowdfunding has a positive and significant effect on business formation while Regulation CF has no effect.

The results in columns (3) and (6) of Table 1.8 show that in a state with an average pre-treatment amount (number) of loans with origination amounts below \$1 million, the passage of intrastate crowdfunding leads to a 2.8% (1.9%) increase in business formation one year after business applications are filed. A 10% decrease in the pre-treatment level of local

[33] The coefficient on the interaction term $En_{ist} * D_{st}$ is negative and significant in all specifications. However, the coefficient on the triple interaction term is not significant.

financial market development leads to a 0.2% increase in these positive effects, suggesting that these effects are stronger in states with less developed financial markets. Table OA-10 in the Online Appendix shows similar but less significant results when other measures of local financial market development are used. Figures OA-43 to OA-48 and OA-49 to OA-54 in the Internet Appendix present results of testing the parallel trend assumptions for all specifications in Tables 1.8 and OA-10. Note that the coefficient related to one of the pre-treatment periods is marginally significant at the 5% level in these tests.

**[See Table 1.8]**

In addition, the results in columns (3) and (6) of Table 1.9 show that after the passage of intrastate crowdfunding in a state with an average pre-treatment amount of loans with origination amounts less than $1 million (average pre-treatment level of bank deposits), business formation within two years after business applications are filed increases by 4.6% (3.4%). These effects increase by 1.1% (0.8%) if the pre-treatment level of local financial market development decreases by 10%. Table OA-11 in the Online Appendix presents similar results but they are less statistically significant for other measures of local financial market development. Figures OA-55 to OA-60 and figures OA-61 to OA-66 show that the parallel trend assumptions can not be rejected for any of the specifications in Tables 1.9 and OA-11.

**[See Table 1.9]**

These results are consistent with the observation that intrastate crowdfunding spurs business applications with planned wages and high propensity business applications but Regulation CF does not have any effect on these type of business applications. In addition, the finding that Regulation CF significantly affects the number of business applications by non-corporations but does not affect employer business formation can help in making some conclusions about these businesses. It is possible that these businesses are not able to raise capital through Regulation CF, that they fail after raising capital through Regulation CF, or that they do not aim at growing (can not grow) to employer businesses.

### 1.5.5 Business Dynamics and Real Economic Outcomes

In this section, I investigate whether access to return-based crowdfunding affects business dynamics and real economic outcomes. The dependent variables are establishment entry, establishment exit, job creation, job destruction, employment by non-farm proprietorships, number of non-employer establishments, and total employment and total annual payroll of employer businesses.

#### Intrastate Crowdfunding

Table 1.10 shows the effect of access to intrastate crowdfunding on employment by non-farm proprietors[34] and on the number of establishments by non-employer businesses. Figures OA-67 to OA-72 in the Online Appendix show that the parallel trend assumption cannot be rejected for any of the regression results in Table 1.10. The results in columns (2) and (5) show that the passage of intrastate crowdfunding in a state with an average pre-treatment level of deposits increases non-farm proprietors' employment by 0.14% ($\approx 1,064$) and non-employer business establishments by 0.32% ($\approx 1,403$). These effects are stronger in states with higher pre-treatment levels of bank deposits. A 10% increase in the pre-treatment level of deposits increases the effect of intrastate crowdfunding on employment by non-farm proprietorships by 0.17% and increases the effect of intrastate crowdfunding on the number of non-employer establishments by 0.13%.

**[See Table 1.10]**

Next, I examine employer business dynamics. The results in columns (2) and (5) in Table 1.11 show that after the passage of intrastate crowdfunding, a state with an average pre-treatment number of loans with origination amounts less than $1 million (average pre-treatment level of bank deposits) experiences a 1.3% (1.4%) increase in job creation by

[34] Non-farm proprietor employment consists of the number of non-farm sole proprietorships and the number of individual general partners in non-farm partnerships. In addition, proprietors can hire employees and there is no limit on the number of employees.

employer businesses. These positive effects increase as the level of local financial market development increases. A 10% increase in the pre-treatment number of loans with origination amounts less than or equal to $1 million (average pre-treatment level of bank deposits) increases these positive effects by 0.26% (0.25%). The results in columns (3) and (6) show that adding $Ln(GDP_{st})$ to the regressions makes coefficients on all the other variables including $Ln(Pop_{st})$ insignificant.

**[See Table 1.11]**

Given that state-level labor income is used in the estimation of state-level GDP, there is a high correlation between the growth in job creation by employer businesses and the growth in state-level GDP. As a result, adding $Ln(GDP_{st})$ to these regressions makes coefficients on other variables insignificant.

Tables OA-12 and OA-13 in the Online Appendix present similar patterns in results when other measures of local financial market development are used. These results show that intrastate crowdfunding exerts a positive effect on job creation by employer businesses. Figures OA-73 to OA-87 show that the parallel trend assumption can not be rejected in any of the specifications in Tables 1.11, OA-12, and OA-13. I also find that intrastate crowdfunding does not have a significant effect on establishment exit or job destruction by all firms. The effect of intrastate crowdfunding on establishment entry by all firms can not be interpreted because the parallel trend assumption does not hold.

Given that the return-based crowdfunding methods under study are aimed at small businesses, I next examine whether or not the effects on business dynamics are driven by small businesses. Using a sub-sample of firms with fewer than 20 employees, I find that intrastate crowdfunding does not have any effect on job creation, job destruction, or establishment exits by these type of firms. This observation suggests that the positive effect of intrastate crowdfunding on job creation is not driven by small businesses.

It is also important to investigate whether these regulations help non-employer startups to grow and become employer businesses or if it helps firms that are already employer businesses to expand or avoid shrinking. The Business Dynamics Statistics (BDS) dataset provides data on establishment entry, establishment exit, job creation, and job destruction for firms at different ages. In this dataset age is the number of years a firm operates after it becomes an employer business. I do not find robust evidence[35] that intrastate crowdfunding has an effect on job creation by firms that just became employer businesses (age zero).[36] Considering the sub-sample of firms that operate one to five years after they become employer businesses, I find that intrastate crowdfunding has a negative effect on job destruction and a small positive effect on job creation. The results in columns (2) and (5) of Table 1.12 show that in a state with average pre-treatment level of bank deposits, the passage of intrastate crowdfunding increases (decreases) job creation (job destruction) by firms operating one to five years after becoming an employer business by 0.05% (5%). Figures OA-88 to OA-93 in the Online Appendix show that the parallel trend assumption holds in all columns in Table 1.12. A 10% decrease in the pre-treatment level of bank deposits decreases the positive effect on job creation by 0.6% and increases the negative effect on job destruction by 0.6%.

**[See Table 1.12]**

Interestingly, the results about the effect of intrastate crowdfunding on non-farm proprietor employment (Table 1.10), the number of non-employer establishments (Table 1.10), and job creation (Tables 1.11 and 1.12) are stronger in states with more developed local financial markets. One possible explanation can be that it is easier to attract workers and entrepreneurs to more financially developed areas, hence labor growth is stronger in these states. It is also possible that the negative effect of competition among entrepreneurs caused by access to crowdfunding is less severe in more financially developed states because businesses have access to other sources of financing. In addition, the supply of capital through crowdfunding may make other sources of financing more affordable for small businesses. Observing that the effect of intrastate crowdfunding on these outcome variables is stronger in states with higher levels of bank deposits suggests that this method of financing may be a channel to transfer funds from wealthier individuals to entrepreneurs in their own states.

[35]Parallel trend assumption does not hold.

[36]Only two variables of job creation and establishment entry are defined for firms with age zero.

Tables OA-16 and OA-17 in the Online Appendix present the results regarding the effect of access to intrastate crowdfunding on total employment by employer businesses and on total annual payroll. However, calculating the average treatment effect on treated states, I do not find a persistent positive or negative effect using all measures of local financial market development. Also, the results in Table OA-18 shows that the effect of access to intrastate crowdfunding on the total amount of payroll at businesses with fewer than 20 employees is significant in only one specification when the level of bank deposits is used to measure local financial market development. Using other measures of local financial market development I do not find any significant effects.

**Regulation CF**

The results in Table 1.13 show that access to Regulation CF leads to a 14.5% (21%) decrease in establishment entry (exit). These effects do not depend on the pre-treatment number of loans to small businesses. Figures OA-94 to OA-102 in the Online Appendix show that tests of the parallel trend assumption can not reject it for the specifications in Table 1.13. In the sub-sample of firms with fewer than 20 employees, I find that Regulation CF only decreases establishment exits and not establishment entry. In other words, Regulation CF helps small businesses avoid shrinking while not preventing other small businesses from growing. The results in Table 1.14 show that after the passage of Regulation CF, establishment exits by firms with fewer than 20 employees decreases on average by 20.8%. I do not find evidence that this effect depends on the level of local financial market development. Figures OA-103 to OA-108 show that the parallel trend assumption can not be rejected for the results in Table 1.14. I also find that the passage of Regulation CF does not have any effect on establishment entry or job creation by firms that just became employer businesses (age zero). However, the results in Table 1.15 show that Regulation CF decreases establishment entry and establishment exit at firms operating for one to five years after becoming employer businesses by 27.8% and 38.4%, respectively. Tables OA-14 and OA-15 provide similar results regarding the effect of Regulation CF on establishment entry and exit by these type of firms. The results of parallel trend analysis for Tables 1.15, OA-14, and OA-15 are presented in Figures OA-109 to OA-126. The finding that Regulation CF affects the entry and exit of firms operating one to five years after becoming an employer businesses suggest that more established businesses are more successful in using Regulation CF to avoid losing their businesses and preventing other businesses from growing. More established firms can likely provide information about their past performance, decreasing information asymmetry and attracting investors.

**[See Table 1.13]**

**[See Table 1.14]**

**[See Table 1.15]**

No results are reported regarding the effect of Regulation CF on employment by non-farm proprietorships, number of non-employer establishments, and total employment and total annual payroll of employer businesses because either parallel trend assumptions do not hold or the results are not significant.

### 1.6 Robustness

In this section, I examine whether the parallel trend assumption can be rejected using the recently proposed estimator by Sun and Abraham (2021). According to these authors, when treatment timing is staggered, it is possible that the treatment effect in one period contaminates the coefficient on a lead or a lag variable in another period, leading to a false pretrend or posttrend. They propose the interaction weighted (IW) estimator to solve this issue. The IW estimator package can be easily used for the dynamic version of equation (1.1) but to use it for the case with continuous pre-treatment variable in equation (1.2) I define a dummy variable that takes a value of 1 when the pre-treatment measure of the local financial market depth is above its median, otherwise it is 0. Then I estimate the following dynamic regression using the IW estimator:

$$Ln(Y_{st}) = \Sigma_{l,l\neq-1}\mu_l * 1\{Measure_{s,l=-1} > Median(Measure_{l=-1})\} * 1\{t - E_s = l\} +$$
$$\Sigma_{l,l\neq-1}\gamma_l * 1\{Measure_{s,l=-1} <= Median(Measure_{l=-1})\} * 1\{t - E_s = l\} + \tau_t + \pi_s + \epsilon_{st}, \tag{1.5}$$

Where $E_s$ is the year in which state $s$ adopts intrastate crowdfunding; $l$ denotes the distance between year $t$ and the first treatment year for state $s$; and $1\{t-E_s = l\}$ is a dummy variable that takes a value equal to one when the distance between year t and the first treatment year for state $s$ is equal to $l$. I drop the dummy variable $1\{t - E_s = -1\}$ for the period before the treatment year to avoid co-linearity. I also add controls for $Ln(Pop_{st})$ and $Ln(GDP_{st})$ step-by-step and check at each step whether or not the parallel trend assumption can be rejected.

Figures (1.8) and (1.9) present the results of testing the parallel trend assumption for column (1) in Table 1.2 using the estimator proposed by Sun and Abraham (2021). These results show the coefficients on the interaction terms in equation (1.5) for states with above and below median pre-treatment amounts of bank loans with origination amounts less than or equal to $1 million. They show that there are no significant pre-trends and that the significant differential effect of intrastate crowdfunding on the total number of business applications comes from the states with a below median pre-treatment level of local financial market development. Figures OA-127 to OA-154 in the Online Appendix show similar results for all other columns in Tables 1.2, OA-1, and OA-2.

**[See Figure 1.8]**

**[See Figure 1.9]**

## 1.7 Conclusion

The role of local financial market development in entrepreneurship and firm growth (

Looking at the sub-samples of business applications shows that both methods spur business applications by non-corporations, such as sole-proprietorships, partnership, and limited liability companies (LLCs), with stronger effects in states with lower levels of local financial market development. This finding suggests that individuals and small firms were prevented from market entry due to frictions in access to financing. I also find that access to intrastate crowdfunding decreases local bias in entrepreneurship (i.e. individuals that work in states other than where they were born are more likely to be self-employed).

The results show that the effects of intrastate crowdfunding and Regulation CF on business formation, business dynamics, and real economic outcomes show considerable differences between the real effects of these two methods of financing. While the effect of intrastate crowdfunding on the number of business applications is considerably smaller than that of Regulation CF, only intrastate crowdfunding has a positive and significant effect on the number of business applications that turn into employer businesses within two years after business applications are filed. This finding suggests that businesses attracted by intrastate crowdfunding may be higher quality or that with-in state investors are more successful at recognizing businesses with more growth prospects.

In addition, the finding that business applications spurred by the passage of Regulation CF do not turn into employer businesses suggests several explanations: 1) these businesses were not successful in raising capital through Regulation CF; 2) these businesses failed after raising capital through Regulation CF; or 3) these businesses do not have the potential to or do not aim to grow to employer businesses. The last explanation is possible because I find that Regulation CF does not have any detectable effect on the number of business applications with planned wages or high-propensity business applications. However, these types of business applications significantly increase after the passage of intrastate crowdfunding. Intrastate crowdfunding may attract businesses with more growth prospects because in several states the maximum financing limit under intrastate crowdfunding is larger than that under Regulation CF. However, it is possible that the observed increase is a result of business relocation from states without intrastate CF to states with intrastate CF.

The results show that intrastate crowdfunding is more effective in increasing job creation, self-employment, and number of establishments by non-employer businesses, and in decreasing job destruction by employer businesses, while Regulation CF decreases establishment exits for small businesses and establismhent entry for other businesses. In addition, I find that established firms are more likely to use Regulation CF. This can happen because these types of firms can alleviate information asymmetry in Regulation CF campaigns and attract investors.

In summary, this paper shows that return-based crowdfunding increases entrepreneurial entry by individuals and small businesses, especially in states with less developed financial markets. By comparing the effects of state level and federal level regulations on business formation, business dynamics, and real economic outcomes, this paper provides some guidance for future policies aimed at spurring entrepreneurial activities and the growth of small businesses.

## 1.8 Tables and Figures

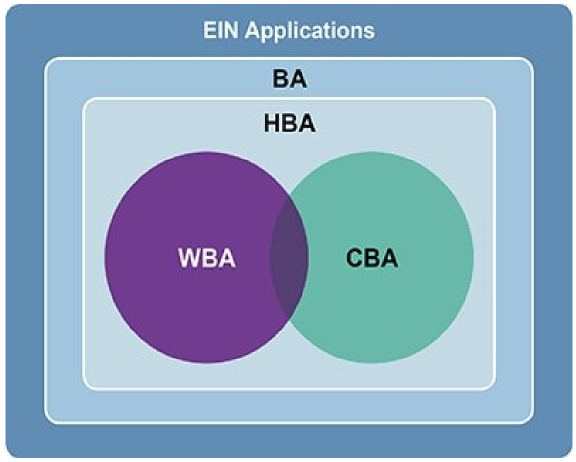


**Figure 1.1. The Relationship Between Different Business Applications Series**

This figure shows a Venn diagram of the relationship between the four business applications series (BA, HBA, WBA, CBA) and EIN applications. EIN applications are applications for Employer Identification Number (EIN) through filing IRS Form SS-4. The main Business Applications (BA) series describes a subset of all EIN applications. EIN applications excluded from the main Business Applications (BA) series include applications for tax liens, estates, trusts, or certain financial filings, applications outside of 50 states and DC, applications with certain NAICS codes in sector 11 (agriculture, forestry, fishing and hunting) or 92 (public administration), and applications in industries such as private households, civic and social organizations. High-Propensity Business (HBA) Applications are Business Applications (BA) that are more probable to turn into employer businesses with payroll. These applications include Business Applications (BA) by corporations, Business Applications (BA) that indicate they are hiring employees, Business Applications that indicate a planned date to pay wages or a first wages-paid date on the IRS Form SS-4, Business Applications (BA) in certain industries. Business Applications with Planned Wages (WBA) are High-Propensity Business Applications (HBA) that indicate a planned date to pay wages or a first wages-paid date. Business Applications from Corporations (CBA) are filed by corporations or personal service corporations.

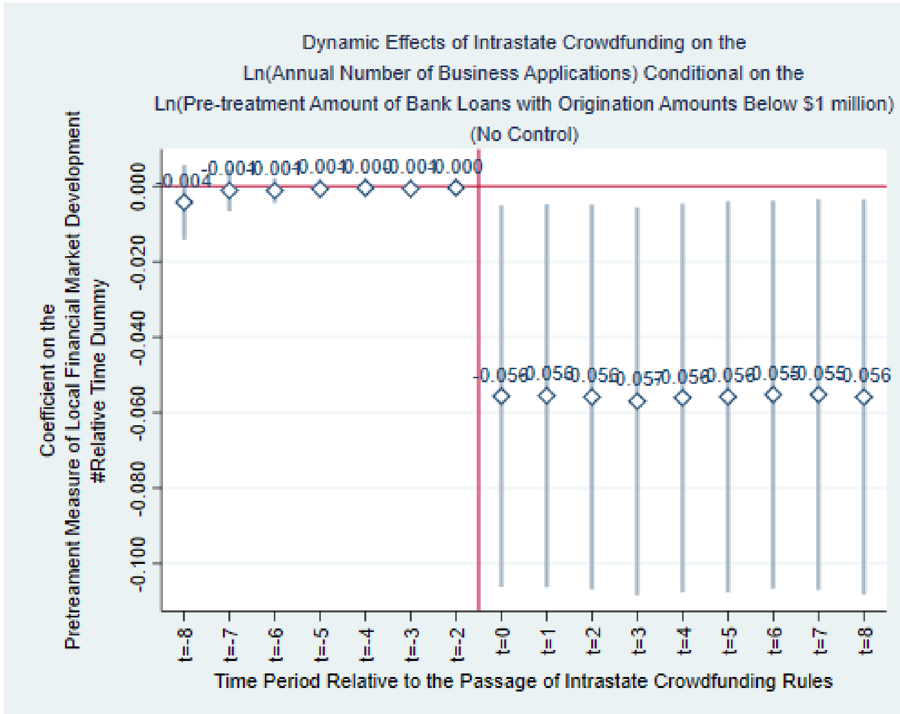


**Figure 1.2. Dynamic Effect of Intrastate Crowdfunding (without Control Variables)**

This figure shows the dynamic effects of introducing intrastate crowdfunding on the log number of business applications using the following dynamic differences-in-differences regression model with continuous treatment:

$$Ln(Y_{st}) = \Sigma_{l,l\neq-1}\mu_l * Ln(Measure_{s,l=-1}) * 1\{t - E_s = l\} + \beta * D_{st} + \tau_t + \pi_s + \epsilon_{st}$$

$Y_{st}$ is the number of business applications in state $s$ in year $t$. $E_s$ is the year in which state s adopts intrastate crowdfunding. $l$ shows the distance between year t and the first treatment year for state s. $1\{t - E_s = l\}$ is a dummy variable that gets value equal to one when the distance between year t and the first treatment year for state s is equal to $l$. I drop the dummy variable for the period before the treatment year $1\{t - E_s = -1\}$ to avoid co-linearity. Here, $Ln(Measure_{s,l=-1})$ denotes log amount of loans with origination amounts less than or equal to $1 million in the year before a state adopts intrastate crowdfunding. $D_{s,t}$ is a dummy equaling 1 if state s has intrastate crowdfunding regulations in year t. No control variable is included in this dynamic regression. $\pi_t$ and $\pi_s$ are year and state fixed effects. The sample period is 2009 to 2019. The rhombuses denote the point estimates of $\mu_l$ and the bars indicate 95% confidence intervals.

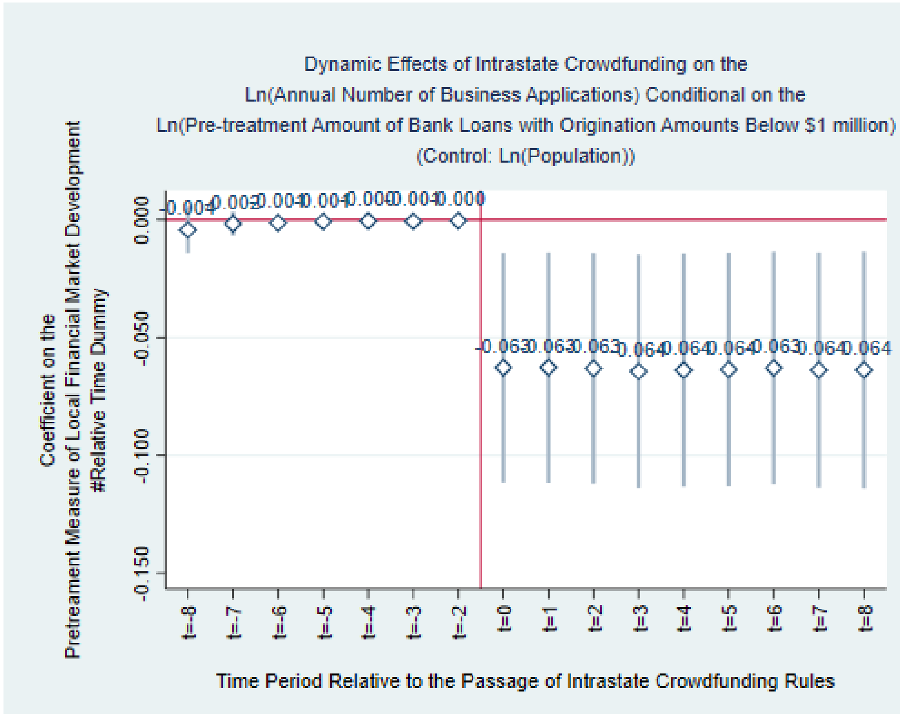


**Figure 1.3. Dynamic Effect of Intrastate Crowdfunding (with Control Variable for Population)**

This figure shows the dynamic effect of introducing intrastate crowdfunding on the log number of business applications using the following dynamic differences-in-differences regression model with continuous treatment:

$$Ln(Y_{st}) = \Sigma_{l,l\neq -1}\mu_l * Ln(Measure_{s,l=-1}) * 1\{t - E_s = l\} + \beta * D_{st} + Ln(Pop_{s,t}) + \tau_t + \pi_s + \epsilon_{st}$$

$Y_{st}$ is the number of business applications in state $s$ in year $t$. $E_s$ is the year in which state s adopts intrastate crowdfunding. $l$ shows the distance between year t and the first treatment year for state s. $1\{t - E_s = l\}$ is a dummy variable that gets value equal to one when the distance between year t and the first treatment year for state s is equal to $l$. I drop the dummy variable for the period before the treatment year $1\{t - E_s = -1\}$ to avoid co-linearity. Here, $Ln(Measure_{s,l=-1})$ denotes log amount of loans with origination amounts less than or equal to $1 million in the year before a state adopts intrastate crowdfunding. $D_{s,t}$ is a dummy equaling 1 if state s has intrastate crowdfunding regulations in year t. Log of population ($Ln(Pop_{s,t})$) is included in this dynamic regression. $\pi_t$ and $\pi_s$ are year and state fixed effects. The sample period is 2009 to 2019. The rhombuses denote the point estimates of $\mu_l$ and the bars indicate 95% confidence intervals.

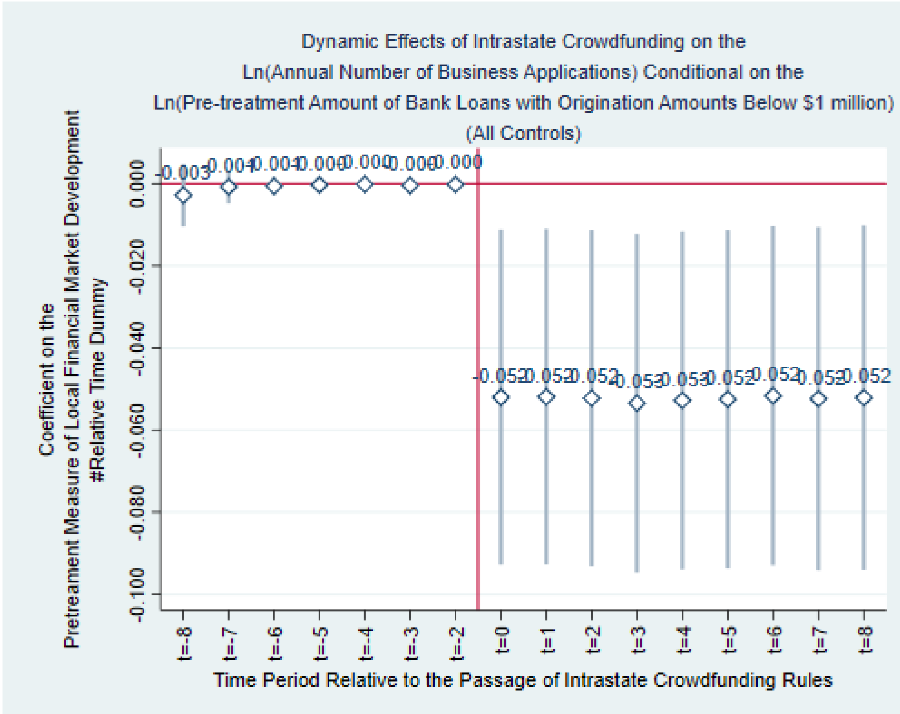


**Figure 1.4. Dynamic Effect of Intrastate Crowdfunding (with All Control Variables)**

This figure shows the dynamic effect of introducing intrastate crowdfunding on the log number of business applications using the following dynamic differences-in-differences regression model with continuous treatment:

$Ln(Y_{st}) = \Sigma_{l,l\neq-1}\mu_l * Ln(Measure_{s,l=-1}) * 1\{t - E_s = l\} + \beta * D_{st} + Ln(Pop_{s,t}) + Ln(GDP_{s,t}) + \tau_t + \pi_s + \epsilon_{st}$

$Y_{st}$ is the number of business applications in state $s$ in year $t$. $E_s$ is the year in which state s adopts intrastate crowdfunding. $l$ shows the distance between year t and the first treatment year for state s. $1\{t - E_s = l\}$ is a dummy variable that gets value equal to one when the distance between year t and the first treatment year for state s is equal to $l$. I drop the dummy variable for the period before the treatment year $1\{t - E_s = -1\}$ to avoid co-linearity. Here, $Ln(Measure_{s,l=-1})$ denotes log amount of loans with origination amounts less than or equal to $1 million in the year before a state adopts intrastate crowdfunding. $D_{s,t}$ is a dummy equaling 1 if state s has intrastate crowdfunding regulations in year t. Log of population ($Ln(Pop_{s,t})$) and log of GDP ($Ln(GDP_{s,t})$) are included in this dynamic regression. $\pi_t$ and $\pi_s$ are year and state fixed effects. The sample period is 2009 to 2019. The rhombuses denote the point estimates of $\mu_l$ and the bars indicate 95% confidence intervals.

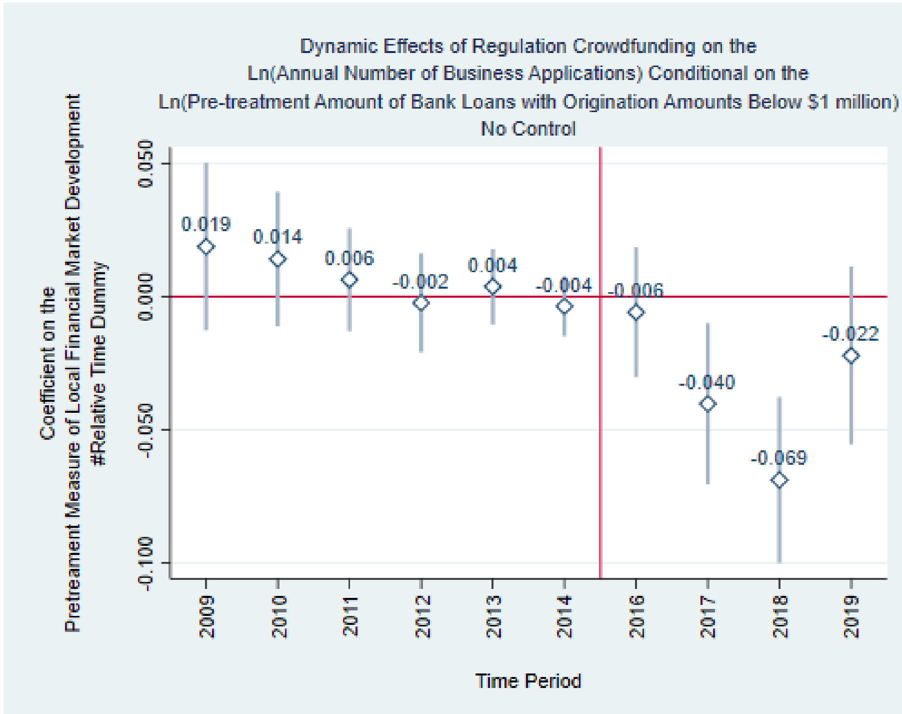


**Figure 1.5. Dynamic Effect of Regulation CF (without Control Variables)**

This figure shows the dynamic effect of introducing Regulation CF on the log number of business applications using the following dynamic differences-in-differences regression model with continuous treatment:

$$Ln(Y_{st}) = \Sigma_{l,l\neq -1}\mu_l * Ln(Measure_{s,l=-1}) * 1\{t - E_s = l\} + \beta * D_{st} + \tau_t + \pi_s + \epsilon_{st}$$

$Y_{st}$ is the number of business applications in state $s$ in year $t$. $E_s$ is year 2016, the year in which Regulation CF became effective. $l$ shows the distance between year t and year 2016. $1\{t - E_s = l\}$ is a dummy variable that gets value equal to one when the distance between year t and year 2016 is equal to $l$. I drop the dummy variable for 2015 ($1\{t - E_s = -1\}$) to avoid co-linearity. Here, $Ln(Measure_{s,l=-1})$ denotes log amount of loans with origination amounts less than or equal to \$1 million in 2015, the year before the passage of Regulation CF. $D_{s,t}$ is a dummy equaling 1 for all states s from 2016 onward. No control variable is included in this dynamic regression. $\pi_t$ and $\pi_s$ are year and state fixed effects. The sample period is 2009 to 2019. The rhombuses denote the point estimates of $\mu_l$ and the bars indicate 95% confidence intervals.

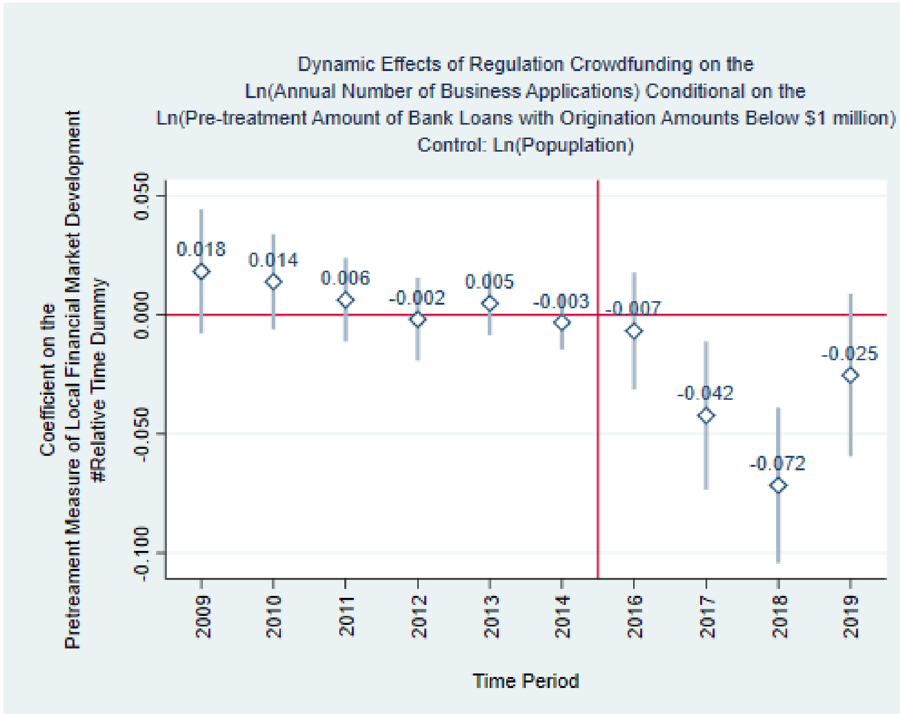


**Figure 1.6. Dynamic Effect of Regulation CF (with Control Variable for Population)**

This figure shows the dynamic effect of introducing Regulation CF on the log number of business applications using the following dynamic differences-in-differences regression model with continuous treatment:

$$Ln(Y_{st}) = \Sigma_{l,l\neq-1}\mu_l * Ln(Measure_{s,l=-1}) * 1\{t - E_s = l\} + \beta * D_{st} + Ln(Pop_{s,t}) + \tau_t + \pi_s + \epsilon_{st}$$

$Y_{st}$ is the number of business applications in state $s$ in year $t$. $E_s$ is year 2016, the year in which Regulation CF became effective. $l$ shows the distance between year t and year 2016. $1\{t - E_s = l\}$ is a dummy variable that gets value equal to one when the distance between year t and year 2016 is equal to $l$. I drop the dummy variable for 2015 ($1\{t - E_s = -1\}$) to avoid co-linearity. Here, $Ln(Measure_{s,l=-1})$ denotes log amount of loans with origination amounts less than or equal to \$1 million in 2015, the year before the passage of Regulation CF. $D_{s,t}$ is a dummy equaling 1 for all states from 2016 onward. Log of population ($Ln(Pop_{s,t})$) is included in this dynamic regression. $\pi_t$ and $\pi_s$ are year and state fixed effects. The sample period is 2009 to 2019. The rhombuses denote the point estimates of $\mu_l$ and the bars indicate 95% confidence intervals.

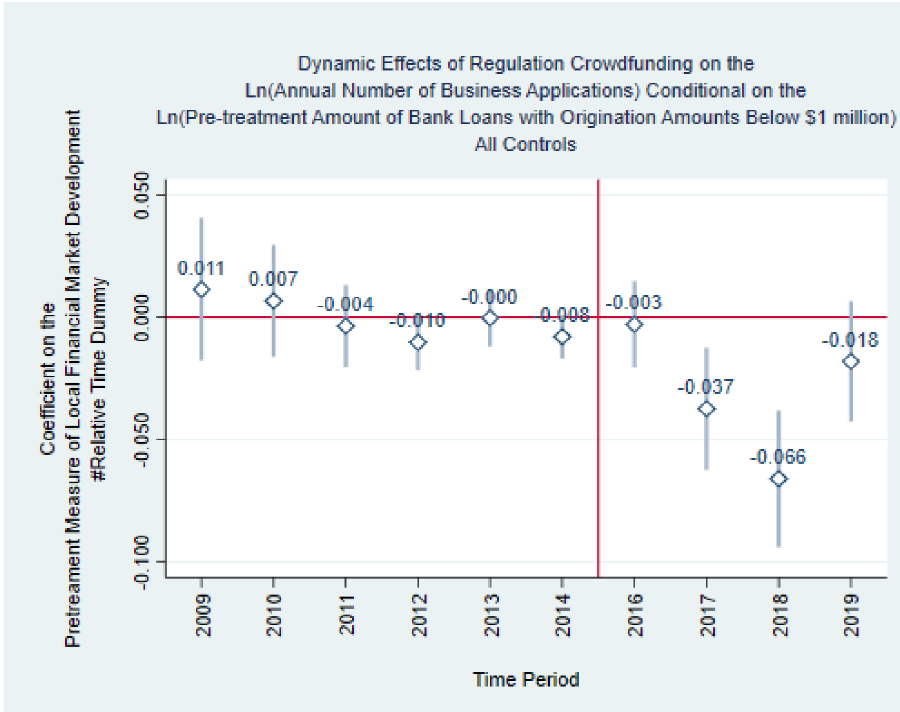


**Figure 1.7. Dynamic Effect of Regulation CF (with All Control Variables)**

This figure shows the dynamic effect of introducing Regulation CF on the log number of business applications using the following dynamic differences-in-differences regression model with continuous treatment:

$$Ln(Y_{st}) = \Sigma_{l,l\neq-1}\mu_l * Ln(Measure_{s,l=-1}) * 1\{t - E_s = l\} + \beta * D_{st} + Ln(Pop_{s,t}) + Ln(GDP_{s,t}) + \tau_t + \pi_s + \epsilon_{st}$$

$Y_{st}$ is the number of business applications in state $s$ in year $t$. $E_s$ is year 2016, the year in which Regulation CF became effective. $l$ shows the distance between year t and year 2016. $1\{t - E_s = l\}$ is a dummy variable that gets value equal to one when the distance between year t and year 2016 is equal to $l$. I drop the dummy variable for 2015 ($1\{t - E_s = -1\}$) to avoid co-linearity. Here, $Ln(Measure_{s,l=-1})$ denotes log amount of loans with origination amounts less than or equal to $1 million in 2015, the year before the passage of Regulation CF. $D_{s,t}$ is a dummy equaling 1 for all states from 2016 onward. Log of population ($Ln(Pop_{s,t})$) and log of GDP ($Ln(GDP_{s,t})$) are included in this dynamic regression. $\pi_t$ and $\pi_s$ are year and state fixed effects. The sample period is 2009 to 2019. The rhombuses denote the point estimates of $\mu_l$ and the bars indicate 95% confidence intervals.

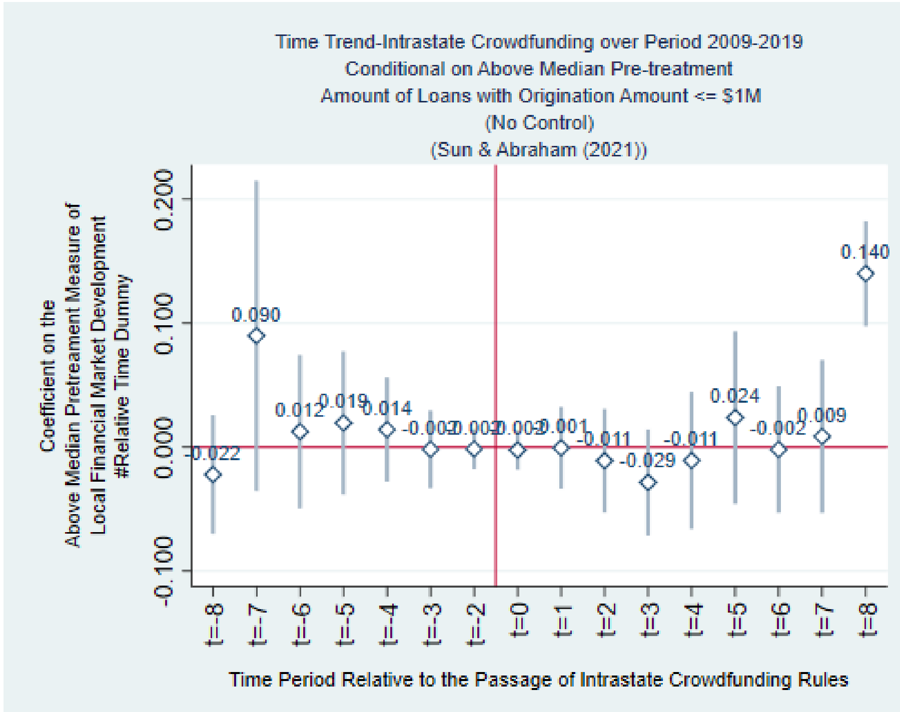


**Figure 1.8. Dynamic Effect of Intrastate Crowdfunding on States with Above-median Local Financial Market Development**

This figure shows the dynamic effect of introducing intrastate crowdfunding on the log number of business applications using the dynamic differences-in-differences regression model in equation (1.5). The rhombuses denote the point estimates of dynamic coefficients ($\mu_l$) for states with above-median pre-treatment measures of local financial market development, and the bars indicate 95% confidence intervals. These coefficients are estimated using the interaction weighted (IW) estimator proposed by Sun and Abraham (2021). The year before adoption of intrastate crowdfunding in each state is dropped. Here, the pre-treatment measure of local financial market development is log amount of loans with origination amounts less than or equal to $1 million in the year before a state adopts intrastate crowdfunding. State and time fixed effects are used, and the sample period is 2009 to 2019.

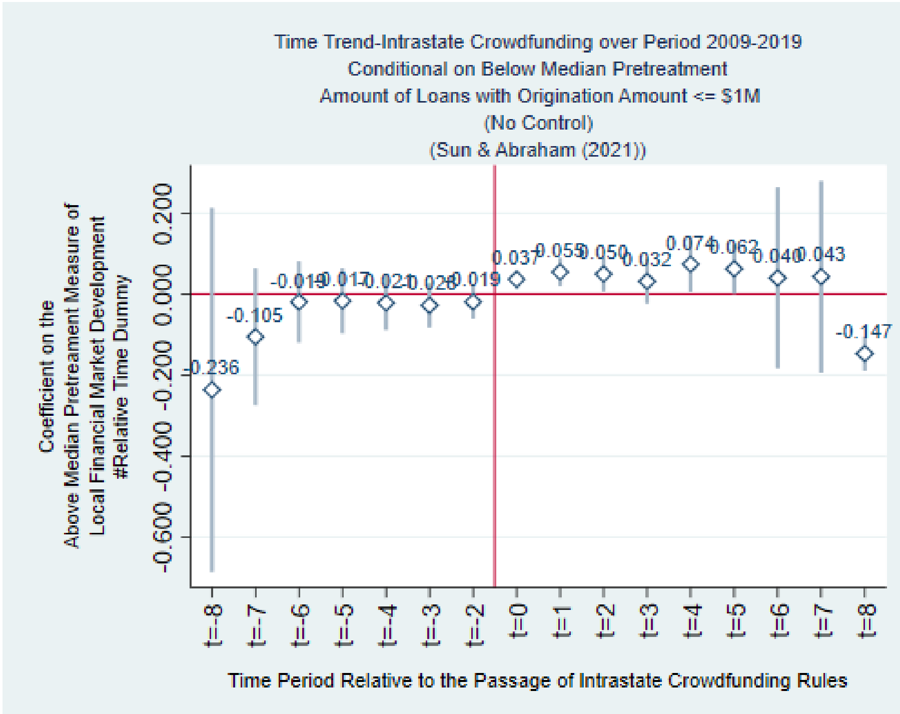


**Figure 1.9. Dynamic Effect of Intrastate Crowdfunding on States with Below-median Local Financial Market Development**

This figure shows the dynamic effect of introducing intrastate crowdfunding on the log number of business applications using the dynamic differences-in-differences regression model in equation (1.5). The rhombuses denote the point estimates of dynamic coefficients ($\lambda_l$) for states with below-median pre-treatment measures of local financial market development, and the bars indicate 95% confidence intervals. These coefficients are estimated using the interaction weighted (IW) estimator proposed by Sun and Abraham (2021). The year before adoption of intrastate crowdfunding in each state is dropped. Here, the pre-treatment measure of local financial market development is log amount of loans with origination amounts less than or equal to $1 million in the year before a state adopts intrastate crowdfunding. State and time fixed effects are used, and the sample period is 2009 to 2019.

**Table 1.1. List of States/Territories with Intrastate Crowdfunding**

This table lists the 35 states/territories in the U.S. that adopted intrastate crowdfunding from 2009 to 2019.

| State | Effective Year | State | Effective Year |
|---|---|---|---|
| Alabama (AL) | 2014 | Michigan (MI) | 2013 |
| Alaska (AK) | 2016 | Minnesota (MN) | 2016 |
| Arizona (AZ) | 2015 | Mississippi (MS) | 2015 |
| Arkansas (AR)[a] | 2017 | Montana (MO) | 2015 |
| Colorado (CO) | 2015 | Nebraska (NE) | 2015 |
| Delaware (DE) | 2016 | New Jersey (NJ) | 2016 |
| District of Columbia (DC) | 2014 | North Carolina (NC) | 2017 |
| Florida (FL) | 2015 | Oregon (OR) | 2015 |
| Georgia (GA) | 2011 | South Carolina (SC) | 2015 |
| Idaho (ID) | 2012 | Tennessee (TN) | 2015 |
| Illinois (IL) | 2016 | Texas (TX) | 2014 |
| Indiana (IN) | 2014 | Vermont (VT) | 2014 |
| Iowa (IA) | 2016 | Virginia (VA) | 2015 |
| Kansas (KS) | 2011 | Washington (WA) | 2014 |
| Kentucky (KY) | 2015 | West Virginia (WV) | 2016 |
| Main (ME) | 2015 | Wisconsin (WI) | 2014 |
| Maryland (MD) | 2014 | Wyoming (WY) | 2017 |
| Massachusetts (MA) | 2015 | | |

[a]HB 1800 was signed into law on March 28, 2017, and became effective on August 1, 2017. See legiscan.com/AR/text/HB1800/id/1576555/Arkansas-2017-HB1800-Chaptered.pdf.

**Table 1.2. The Effect of Intrastate Crowdfunding on the Total Number of Business Applications**

This table reports the differences-in-differences estimates for the effect of intrastate crowdfunding on the number of business applications conditional on the pre-treatment measures of local financial market development. The dependent variable is log number of business applications. The observations are at the state-year level, and the sample period is 2009 to 2019. $D_{s,t}$ is an indicator equaling one if state $s$ has intrastate crowdfunding in year $t$. $Ln(AmountLoanLEQ1M_{pretreatment})$ is log amount of loans with origination amounts less than or equal to $1 million and $Ln(Deposit_{pretreatment})$ is log of total deposits in the year before a state adopts intrastate crowdfunding. $Ln(Pop_{s,t})$ is log of population and $Ln(GDP_{s,t})$ is log of GDP in state $s$ and year $t$. All specifications include state and year fixed effects. Standard errors are clustered at the state level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

| | Ln(No Business Applications) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $D_{s,t}$ | 1.238** | 1.398** | 1.142** | 0.971 | 1.170** | 0.921** |
| | (0.574) | (0.558) | (0.439) | (0.592) | (0.549) | (0.420) |
| $Ln(AmountLoanLEQ1M_{pretreatment}) * D_{s,t}$ | -0.056** | -0.064** | -0.052** | | | |
| | (0.026) | (0.026) | (0.020) | | | |
| $Ln(Deposit_{pretreatment}) * D_{s,t}$ | | | | -0.038 | -0.046** | -0.036** |
| | | | | (0.023) | (0.022) | (0.017) |
| $Ln(Pop_{s,t})$ | | 0.998*** | 1.474*** | | 0.986*** | 1.558*** |
| | | (0.346) | (0.518) | | (0.300) | (0.505) |
| $Ln(GDP_{s,t})$ | | | -0.382 | | | -0.456 |
| | | | (0.346) | | | (0.364) |
| Constant | 10.217*** | -4.857 | -7.456 | 10.217*** | -4.676 | -7.834 |
| | (0.012) | (5.235) | (5.557) | (0.012) | (4.535) | (4.987) |
| Observations | 561 | 561 | 561 | 561 | 561 | 561 |
| R-squared | 0.839 | 0.852 | 0.859 | 0.830 | 0.843 | 0.854 |
| Number of States/Territories | 51 | 51 | 51 | 51 | 51 | 51 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Clustered SE (State Level) | Yes | Yes | Yes | Yes | Yes | Yes |

*** p<0.01, ** p<0.05, * p<0.1

**Table 1.3. The Effect of Regulation CF on the Total Number of Business Applications**

This table reports the differences-in-differences estimates for the effect of Regulation CF on the number of business applications conditional on the pre-treatment measures of local financial market development. The dependent variable is log number of business applications. The observations are at the state-year level, and the sample period is 2009 to 2019. $D_{s,t}$ is an indicator equaling one for all states from 2016 onward. $Ln(AmountLoanLEQ1M_{pretreatment})$ is log amount of loans with origination amounts less than or equal to \$1 million and $Ln(Deposit_{pretreatment})$ is log of total deposits in 2015 (the year before the passage of Regulation CF). $Ln(Pop_{s,t})$ is log of population and $Ln(GDP_{s,t})$ is log of GDP in state $s$ and year $t$. All specifications include state and year fixed effects. Standard errors are clustered at the state level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

| | Ln(No Business Applications) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $D_{s,t}$ | 1.228*** | 1.224*** | 1.081*** | 1.140*** | 1.198*** | 1.068*** |
| | (0.415) | (0.419) | (0.296) | (0.403) | (0.392) | (0.278) |
| $Ln(AmountLoanLEQ1M_{pretreatment}) * D_{s,t}$ | -0.040** | -0.042** | -0.030** | | | |
| | (0.019) | (0.019) | (0.012) | | | |
| $Ln(Deposit_{pretreatment}) * D_{s,t}$ | | | | -0.030* | -0.035** | -0.025*** |
| | | | | (0.016) | (0.015) | (0.009) |
| $Ln(Pop_{s,t})$ | | 0.877** | 1.381*** | | 0.963*** | 1.473*** |
| | | (0.329) | (0.489) | | (0.290) | (0.502) |
| $Ln(GDP_{s,t})$ | | | -0.392 | | | -0.414 |
| | | | (0.356) | | | (0.365) |
| Constant | 10.217*** | -3.033 | -5.929 | 10.217*** | -4.328 | -7.057 |
| | (0.012) | (4.970) | (4.978) | (0.012) | (4.386) | (4.792) |
| Observations | 561 | 561 | 561 | 561 | 561 | 561 |
| R-squared | 0.835 | 0.845 | 0.852 | 0.831 | 0.844 | 0.852 |
| Number of States/Territories | 51 | 51 | 51 | 51 | 51 | 51 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Clustered SE (State Level) | Yes | Yes | Yes | Yes | Yes | Yes |
| *** p<0.01, ** p<0.05, * p<0.1 | | | | | | |

**Table 1.4. The Effect of Intrastate Crowdfunding on the Number of Business Applications by Non-corporations**

This table reports the differences-in-differences estimates for the effect of intrastate crowdfunding on the number of business applications by non-corporations conditional on the pre-treatment measures of local financial market development. The dependent variable is log number of business applications by non-corporations. The observations are at the state-year level, and the sample period is 2009 to 2019. $D_{s,t}$ is an indicator equaling one if state $s$ has intrastate crowdfunding in year $t$. $Ln(AmountLoanLEQ1M_{pretreatment})$ is log amount of loans with origination amounts less than or equal to $1 million and $Ln(Deposit_{pretreatment})$ is log of total deposits in the year before a state adopts intrastate crowdfunding. $Ln(Pop_{s,t})$ is log of population and $Ln(GDP_{s,t})$ is log of GDP in state $s$ and year $t$. All specifications include state and year fixed effects. Standard errors are clustered at the state level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

| | Ln(No. Business Applications By Non-Corporations) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $D_{s,t}$ | 1.135* | 1.327** | 1.043** | 0.884 | 1.124* | 0.857* |
| | (0.631) | (0.616) | (0.491) | (0.645) | (0.598) | (0.464) |
| $Ln(AmountLoanLEQ1M_{pretreatment}) * D_{s,t}$ | -0.052* | -0.061** | -0.048** | | | |
| | (0.029) | (0.028) | (0.022) | | | |
| $Ln(Deposit_{pretreatment}) * D_{s,t}$ | | | | -0.034 | -0.044* | -0.033* |
| | | | | (0.026) | (0.024) | (0.018) |
| $Ln(Pop_{s,t})$ | | 1.196*** | 1.724*** | | 1.187*** | 1.801*** |
| | | (0.369) | (0.547) | | (0.317) | (0.530) |
| $Ln(GDP_{s,t})$ | | | -0.424 | | | -0.489 |
| | | | (0.360) | | | (0.377) |
| Constant | 9.995*** | -8.079 | -10.959* | 9.995*** | -7.940 | -11.328** |
| | (0.013) | (5.570) | (5.937) | (0.014) | (4.783) | (5.320) |
| Observations | 561 | 561 | 561 | 561 | 561 | 561 |
| R-squared | 0.864 | 0.878 | 0.884 | 0.859 | 0.872 | 0.881 |
| Number of States/Territories | 51 | 51 | 51 | 51 | 51 | 51 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Clustered SE (State Level) | Yes | Yes | Yes | Yes | Yes | Yes |

*** p<0.01, ** p<0.05, * p<0.1

**Table 1.5. The Effect of Regulation CF on the Number of Business Applications by Non-corporations**

This table reports the differences-in-differences estimates for the effect of Regulation CF on the number of business applications by non-corporations conditional on the pre-treatment measures of local financial market development. The dependent variable is log number of business applications by non-corporations. The observations are at the state-year level, and the sample period is 2009 to 2019. $D_{s,t}$ is an indicator equaling one for all states from 2016 onward. $Ln(AmountLoanLEQ1M_{pretreatment})$ is log amount of loans with origination amounts less than or equal to $1 million and $Ln(Deposit_{pretreatment})$ is log of total deposits in 2015 (the year before the passage of Regulation CF). $Ln(Pop_{s,t})$ is log of population and $Ln(GDP_{s,t})$ is log of GDP in state $s$ and year $t$. All specifications include state and year fixed effects. Standard errors are clustered at the state level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

| | Ln(No. Business Applications By Non-Corporations) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $D_{s,t}$ | 1.384*** | 1.380*** | 1.232*** | 1.262*** | 1.333*** | 1.197*** |
| | (0.434) | (0.436) | (0.314) | (0.421) | (0.407) | (0.290) |
| $Ln(AmountLoanLEQ1M_{pretreatment}) * D_{s,t}$ | -0.042** | -0.045** | -0.033** | | | |
| | (0.020) | (0.019) | (0.013) | | | |
| $Ln(Deposit_{pretreatment}) * D_{s,t}$ | | | | -0.031* | -0.037** | -0.027*** |
| | | | | (0.016) | (0.015) | (0.010) |
| $Ln(Pop_{s,t})$ | | 1.093*** | 1.611*** | | 1.182*** | 1.714*** |
| | | (0.349) | (0.523) | | (0.312) | (0.527) |
| $Ln(GDP_{s,t})$ | | | -0.403 | | | -0.432 |
| | | | (0.366) | | | (0.376) |
| Constant | 9.995*** | -6.527 | -9.500* | 9.995*** | -7.864 | -10.710** |
| | (0.013) | (5.272) | (5.413) | (0.013) | (4.716) | (5.169) |
| Observations | 561 | 561 | 561 | 561 | 561 | 561 |
| R-squared | 0.865 | 0.877 | 0.882 | 0.862 | 0.875 | 0.882 |
| Number of States/Territories | 51 | 51 | 51 | 51 | 51 | 51 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Clustered SE (State Level) | Yes | Yes | Yes | Yes | Yes | Yes |

*** p<0.01, ** p<0.05, * p<0.1

**Table 1.6. The Effect of Intrastate Crowdfunding on the Number of Business Applications with Planned Wages and the Number of High Propensity Business Applications**

This table reports the differences-in-differences estimates for the effect of intrastate crowdfunding on the number of business applications with planned wages and on the number of high propensity business applications conditional on the pre-treatment measures of local financial market development. The dependent variable in columns (1) to (3) is log number of business applications with planned wages, and the dependent variable in columns (4) to (6) is log number of high propensity business applications. The observations are at the state-year level, and the sample period is 2009 to 2019. $D_{s,t}$ is an indicator equaling one if state $s$ has intrastate crowdfunding in year $t$. $Ln(AmountLoanLEQ1M_{pretreatment})$ is log amount of loans with origination amounts less than or equal to \$1 million in the year before a state adopts intrastate crowdfunding. $Ln(Pop_{s,t})$ is log of population and $Ln(GDP_{s,t})$ is log of GDP in state $s$ and year $t$. All specifications include state and year fixed effects. Standard errors are clustered at the state level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

| | Ln(No. Business Applications With Planned Wages) | | | Ln(No. High Propensity Business Applications) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $D_{s,t}$ | 0.499 | 0.692* | 0.789** | 0.652 | 0.787* | 0.741** |
| | (0.332) | (0.357) | (0.357) | (0.435) | (0.407) | (0.350) |
| $Ln(AmountLoanLEQ1M_{pretreatment}) * D_{s,t}$ | -0.022 | -0.031* | -0.036** | -0.029 | -0.035* | -0.033** |
| | (0.015) | (0.016) | (0.016) | (0.020) | (0.019) | (0.016) |
| $Ln(Pop_{s,t})$ | | 1.204*** | 1.025** | | 0.840*** | 0.924* |
| | | (0.310) | (0.477) | | (0.290) | (0.473) |
| $Ln(GDP_{s,t})$ | | | 0.144 | | | -0.068 |
| | | | (0.232) | | | (0.290) |
| Constant | 8.787*** | -9.409** | -8.431 | 9.454*** | -3.231 | -3.692 |
| | (0.010) | (4.678) | (5.314) | (0.010) | (4.376) | (4.880) |
| Observations | 561 | 561 | 561 | 561 | 561 | 561 |
| R-squared | 0.490 | 0.574 | 0.578 | 0.338 | 0.389 | 0.391 |
| Number of States/Territories | 51 | 51 | 51 | 51 | 51 | 51 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Clustered SE (State Level) | Yes | Yes | Yes | Yes | Yes | Yes |
| *** p<0.01, ** p<0.05, * p<0.1 | | | | | | |

**Table 1.7. The Effect of Intrastate Crowdfunding on the Local Bias in Entrepreneurship**

This table reports estimates of the effect of intrastate crowdfunding on local bias in entrepreneurship (LBE) conditional on pre-treatment measures of local financial market development using a triple differences-in-differences regression model. The dependent variable is the dummy $Local_{ist}$ equaling one if, in year t, the head of household i works in the state that he was born in. $En_{ist}$ is a dummy equaling one if the head of household is self-employed (including both incorporated and unincorporated businesses). $D_{s,t}$ is a dummy equaling one if state s has intrastate crowdfunding regulations in year t. $Ln(AmountLoanLEQ1M_{pretreatment})$ is log amount of loans with origination amounts less than or equal to $1 million and $Ln(AmountLoanLess1MRev_{pretreatment})$ is log amount of loans to businesses with revenue less than or equal to $1 million. I use samples of American Community Survey from 2009 to 2019. Each observation denotes a head of household. All specifications include state and year fixed effects. Standard errors are clustered at the state level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

| | $1(Local_{ist} == 1)$ | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $En_{ist}$ | -0.0025 | 0.0030 | 0.0004 | -0.0025 | 0.0030 | 0.0004 |
| | (0.0108) | (0.0107) | (0.0112) | (0.0108) | (0.0107) | (0.0112) |
| $D_{s,t}$ | 0.0005 | 0.0011 | 0.0018 | 0.0004 | 0.0011 | 0.0018 |
| | (0.0039) | (0.0035) | (0.0036) | (0.0039) | (0.0035) | (0.0036) |
| $En_{ist} * D_{s,t}$ | -0.0069** | -0.0074** | -0.0082*** | -0.0070** | -0.0075** | -0.0082*** |
| | (0.0030) | (0.0029) | (0.0028) | (0.0030) | (0.0029) | (0.0027) |
| $Ln(AmountLoanLess1MRev_{pretreatment}) * En_{ist}$ | 0.0009 | 0.0006 | 0.0009 | | | |
| | (0.0006) | (0.0006) | (0.0006) | | | |
| $Ln(AmountLoanLess1MRev_{pretreatment}) * D_{s,t}$ | -0.0002 | -0.0001 | -0.0001 | | | |
| | (0.0002) | (0.0002) | (0.0002) | | | |
| $Ln(AmountLoanLess1MRev_{pretreatment}) * En_{ist} * D_{s,t}$ | 0.0000 | 0.0001 | 0.0001 | | | |
| | (0.0001) | (0.0001) | (0.0001) | | | |
| $Ln(AmountLoanLEQ1M_{pretreatment}) * En_{ist}$ | | | | 0.0009 | 0.0006 | 0.0009 |
| | | | | (0.0006) | (0.0006) | (0.0006) |
| $Ln(AmountLoanLEQ1M_{pretreatment}) * D_{s,t}$ | | | | -0.0002 | -0.0001 | -0.0001 |
| | | | | (0.0002) | (0.0001) | (0.0001) |
| $Ln(AmountLoanLEQ1M_{pretreatment}) * En_{ist} * D_{s,t}$ | | | | 0.0000 | 0.0001 | 0.0001 |
| | | | | (0.0001) | (0.0001) | (0.0001) |
| Observations | 6,220,063 | 5,895,340 | 5,302,097 | 6,220,063 | 5,895,340 | 5,302,097 |
| R-squared | 0.1198 | 0.1227 | 0.1310 | 0.1198 | 0.1227 | 0.1310 |
| Education Level Dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Race Dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Race in the sample | All | White-African American/Black | White | All | White-African American/Black | White |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Clustered SE | Yes-State Level | Yes-State Level | Yes-State Level | Yes-State Level | Yes-State Level | Yes-State Level |

**Table 1.8. Intrastate Crowdfunding and Business Formation within One Year after Business Application**

This table reports the differences-in-differences estimates for the effect of intrastate crowdfunding on business formation within one year after business application conditional on the pre-treatment measures of local financial market development. The dependent variable is log number of business applications in year t that lead to employer businesses within one year after business applications are filed. The observations are at the state-year level, and the sample period is 2009 to 2018. $D_{s,t}$ is an indicator equaling one if state $s$ has intrastate crowdfunding in year $t$. $Ln(AmountLoanLEQ1M_{pretreatment})$ is log amount of loans with origination amounts less than or equal to \$1 million and $Ln(NumLoanLEQ1M_{pretreatment})$ is log number of loans with origination amounts less than or equal to \$1 million in the year before a state adopts intrastate crowdfunding. $Ln(Pop_{s,t})$ is log of population and $Ln(GDP_{s,t})$ is log of GDP in state $s$ and year $t$. All specifications include state and year fixed effects. Standard errors are clustered at the state level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

| | Ln(No Business Formation After 1 year) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $D_{s,t}$ | 0.157 | 0.384 | 0.527** | 0.021 | 0.179 | 0.239** |
| | (0.323) | (0.232) | (0.230) | (0.154) | (0.114) | (0.110) |
| $Ln(AmountLoanLEQ1M_{pretreatment}) * D_{s,t}$ | -0.006 | -0.017 | -0.023** | | | |
| | (0.015) | (0.011) | (0.010) | | | |
| $Ln(NumLoanLEQ1M_{pretreatment}) * D_{s,t}$ | | | | 0.000 | -0.014 | -0.020** |
| | | | | (0.014) | (0.010) | (0.010) |
| $Ln(GDP_{s,t})$ | | | 0.231 | | | 0.216 |
| | | | (0.154) | | | (0.156) |
| $Ln(Pop_{s,t})$ | | 1.673*** | 1.392*** | | 1.688*** | 1.430*** |
| | | (0.374) | (0.504) | | (0.382) | (0.509) |
| Constant | 8.045*** | -17.238*** | -15.757** | 8.045*** | -17.461*** | -16.166** |
| | (0.009) | (5.652) | (6.426) | (0.009) | (5.777) | (6.503) |
| Observations | 510 | 510 | 510 | 510 | 510 | 510 |
| R-squared | 0.085 | 0.282 | 0.298 | 0.083 | 0.280 | 0.294 |
| Number of States/Territories | 51 | 51 | 51 | 51 | 51 | 51 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Clustered SE (State Level) | Yes | Yes | Yes | Yes | Yes | Yes |

**Table 1.9. Intrastate Crowdfunding and Business Formation within Two Years after Business Application**

This table reports the differences-in-differences estimates of the effect of intrastate crowdfunding on business formation within two years after business application conditional on the pre-treatment measures of local financial market development. The dependent variable is log number of business applications in year t that lead to employer businesses within two years after business applications are filed. The observations are at the state-year level, and the sample period is 2009 to 2017. $D_{s,t}$ is an indicator equaling one if state $s$ has intrastate crowdfunding in year $t$. $Ln(AmountLoanLEQ1M_{pretreatment})$ is log amount of loans with origination amounts less than or equal to \$1 million and $Ln(Deposit_{pretreatment})$ is log amount of deposits in the year before a state adopts intrastate crowdfunding. $Ln(Pop_{s,t})$ is log of population and $Ln(GDP_{s,t})$ is log of GDP in state $s$ and year $t$. All specifications include state and year fixed effects. Standard errors are clustered at the state level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

| | Ln(No Business Formation After 2 years) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $D_{s,t}$ | 2.335* | 2.534** | 2.258** | 2.003 | 2.300* | 2.032** |
| | (1.165) | (1.242) | (1.068) | (1.282) | (1.276) | (0.968) |
| $Ln(AmountLoanLEQ1M_{pretreatment}) * D_{s,t}$ | -0.106* | -0.115** | -0.102** | | | |
| | (0.054) | (0.057) | (0.048) | | | |
| $Ln(Deposit_{pretreatment}) * D_{s,t}$ | | | | -0.078 | -0.090* | -0.079** |
| | | | | (0.051) | (0.051) | (0.038) |
| $Ln(GDP_{s,t})$ | | | -0.497 | | | -0.590 |
| | | | (1.339) | | | (1.322) |
| $Ln(Pop_{s,t})$ | | 1.885*** | 2.485 | | 1.940*** | 2.651 |
| | | (0.600) | (1.754) | | (0.499) | (1.732) |
| Constant | 7.919*** | -20.557** | -23.649* | 7.919*** | -21.389*** | -25.034** |
| | (0.028) | (9.066) | (12.553) | (0.028) | (7.535) | (11.700) |
| Observations | 459 | 459 | 459 | 459 | 459 | 459 |
| R-squared | 0.100 | 0.111 | 0.115 | 0.094 | 0.105 | 0.111 |
| Number of States/Territories | 51 | 51 | 51 | 51 | 51 | 51 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Clustered SE (State Level) | Yes | Yes | Yes | Yes | Yes | Yes |

**Table 1.10. Intrastate Crowdfunding and Real Economic Outcomes**

This table reports the differences-in-differences estimates of the effect of intrastate crowdfunding on the employment by non-farm proprietors and on the number of non-employer establishments conditional on a pre-treatment measure of local financial market development. The dependent variable in columns (1) to (3) is log employment by non-farm proprietors and the dependent variable in columns (4) to (6) is log number of non-employer establishments. The observations are at the state-year level, and the sample period is 2009 to 2019. $D_{s,t}$ is an indicator equaling one if state $s$ has intrastate crowdfunding in year $t$. $Ln(Deposit_{pretreatment})$ is log amount of deposits in the year before a state adopts intrastate crowdfunding. $Ln(Pop_{s,t})$ is log of population and $Ln(GDP_{s,t})$ is log of GDP in state $s$ and year $t$. All specifications include state and year fixed effects. Standard errors are clustered at the state level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

| | Ln(Non-Farm Proprietor's Employment) | | | Ln(No. of Establishments) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $D_{s,t}$ | -0.718*** | -0.454** | -0.450** | -0.620*** | -0.351** | -0.378*** |
| | (0.258) | (0.185) | (0.177) | (0.228) | (0.137) | (0.131) |
| $Ln(Deposit_{pretreatment}) * D_{s,t}$ | 0.029*** | 0.018** | 0.018** | 0.025*** | 0.014** | 0.015*** |
| | (0.010) | (0.007) | (0.007) | (0.009) | (0.005) | (0.005) |
| $Ln(Pop_{s,t})$ | | 1.153*** | 1.144*** | | 1.330*** | 1.392*** |
| | | (0.166) | (0.199) | | (0.152) | (0.166) |
| $Ln(GDP_{s,t})$ | | | 0.007 | | | -0.050 |
| | | | (0.067) | | | (0.044) |
| Constant | 12.960*** | -4.460* | -4.407 | 12.439*** | -7.657*** | -8.000*** |
| | (0.007) | (2.512) | (2.642) | (0.006) | (2.294) | (2.301) |
| Observations | 612 | 612 | 612 | 561 | 561 | 561 |
| R-squared | 0.769 | 0.866 | 0.866 | 0.788 | 0.906 | 0.907 |
| Number of States/Territories | 51 | 51 | 51 | 51 | 51 | 51 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Clustered SE (State Level) | Yes | Yes | Yes | Yes | Yes | Yes |

*** p<0.01, ** p<0.05, * p<0.1

**Table 1.11. Intrastate Crowdfunding and Business Dynamics (All Firms)**

This table reports the differences-in-differences estimates of the effect of intrastate crowdfunding on job creation by all firms conditional on the pre-treatment measures of local financial market development. The dependent variable is log job creation (excluding self-employment) by all firm. The observations are at the state-year level, and the sample period is 2009 to 2019. $D_{s,t}$ is an indicator equaling one if state $s$ has intrastate crowdfunding in year $t$. $Ln(NLoanLEQ1M_{pretreatment})$ is log number of loans with origination amounts less than or equal to $1 million and $Ln(Deposit_{pretreatment})$ is log amount of deposits in the year before a state adopts intrastate crowdfunding. $Ln(Pop_{s,t})$ is log of population and $Ln(GDP_{s,t})$ is log of GDP in state $s$ and year $t$. All specifications include state and year fixed effects. Standard errors are clustered at the state level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

| | Ln(Job Creation) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $D_{s,t}$ | -0.382*** | -0.285** | -0.080 | -0.879*** | -0.695** | -0.335 |
| | (0.139) | (0.139) | (0.127) | (0.311) | (0.293) | (0.275) |
| $Ln(NLoanLEQ1M_{pretreatment}) * D_{s,t}$ | 0.036*** | 0.027** | 0.009 | | | |
| | (0.012) | (0.013) | (0.011) | | | |
| $Ln(Deposit_{pretreatment}) * D_{s,t}$ | | | | 0.035*** | 0.028** | 0.014 |
| | | | | (0.012) | (0.012) | (0.011) |
| $Ln(Pop_{s,t})$ | | 0.906*** | 0.088 | | 0.911*** | 0.085 |
| | | (0.260) | (0.330) | | (0.275) | (0.328) |
| $Ln(GDP_{s,t})$ | | | 0.671*** | | | 0.659*** |
| | | | (0.106) | | | (0.117) |
| Constant | 11.982*** | -1.711 | 2.575 | 11.982*** | -1.784 | 2.777 |
| | (0.011) | (3.936) | (4.130) | (0.011) | (4.152) | (4.035) |
| Observations | 561 | 561 | 561 | 561 | 561 | 561 |
| R-squared | 0.527 | 0.561 | 0.632 | 0.529 | 0.565 | 0.635 |
| Number of States/Territories | 51 | 51 | 51 | 51 | 51 | 51 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Clustered SE (State Level) | Yes | Yes | Yes | Yes | Yes | Yes |

**Table 1.12. Intrastate Crowdfunding and Business Dynamics (Young Employer Firms)**

This table reports the differences-in-differences estimates of the effect of intrastate crowdfunding on job creation and destruction by young employer businesses conditional on a pre-treatment measure of local financial market development. The dependent variable in columns (1) to (3) is log job creation (excluding self-employment) by firms that are still active one to five years after becoming an employer business. The dependent variable in columns (4) to (6) is log job destruction (excluding self-employment) by firms that are still active one to five years after becoming an employer business. The observations are at the state-year level, and the sample period is 2009 to 2019. $D_{s,t}$ is an indicator equaling one if state $s$ has intrastate crowdfunding in year $t$. $Ln(NLoanLEQ1M_{pretreatment})$ is log number of loans with origination amounts less than or equal to $1 million and $Ln(Deposit_{pretreatment})$ is log amount of deposits in the year before a state adopts intrastate crowdfunding. $Ln(Pop_{s,t})$ is log of population and $Ln(GDP_{s,t})$ is log of GDP in state $s$ and year $t$. All specifications include state and year fixed effects. Standard errors are clustered at the state level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

| | Ln(Job Creation by Firms with Age 1-5 Years) | | | Ln(Job Destruction by Firms with Age 1-5 Years) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $D_{s,t}$ | -1.440*** | -1.138*** | -0.738 | -1.663*** | -1.418*** | -1.359*** |
| | (0.409) | (0.372) | (0.462) | (0.478) | (0.462) | (0.490) |
| $Ln(Deposit_{pretreatment}) * D_{s,t}$ | 0.057*** | 0.045*** | 0.030 | 0.064*** | 0.054*** | 0.052*** |
| | (0.016) | (0.015) | (0.018) | (0.019) | (0.018) | (0.019) |
| $Ln(Pop_{s,t})$ | | 1.495*** | 0.576 | | 1.214** | 1.080** |
| | | (0.275) | (0.421) | | (0.487) | (0.534) |
| $Ln(GDP_{s,t})$ | | | 0.733*** | | | 0.106 |
| | | | (0.168) | | | (0.179) |
| Constant | 9.999*** | -12.592*** | -7.517 | 10.535*** | -7.804 | -7.067 |
| | (0.014) | (4.146) | (4.905) | (0.015) | (7.370) | (7.437) |
| Observations | 561 | 561 | 561 | 561 | 561 | 561 |
| R-squared | 0.154 | 0.217 | 0.274 | 0.717 | 0.730 | 0.731 |
| Number of States/Territories | 51 | 51 | 51 | 51 | 51 | 51 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Clustered SE (State Level) | Yes | Yes | Yes | Yes | Yes | Yes |

**Table 1.13. Regulation CF and Business Dynamics (All Firms)**

This table reports the differences-in-differences estimates of the effect of Regulation CF on establishment entry and exit by all firms conditional on the pre-treatment measures of local financial market development. The dependent variable in columns (1) to (3) is log of establishment entry by all firm, and the dependent variable in columns (4) to (9) is log of establishment exits by all firm. The observations are at the state-year level, and the sample period is 2009 to 2019. $D_{s,t}$ is an indicator equaling one from 2016 onward for all states. $Ln(NLoanLess1MRev_{pretreatment})$ is log number of loans to businesses with revenue less than or equal to $1 million and $Ln(NLoanLEQ1M_{pretreatment})$ is log number of loans with origination amounts less than or equal to $1 million in 2015 (the year before the passage of Regulation CF). $Ln(Pop_{s,t})$ is log of population and $Ln(GDP_{s,t})$ is log of GDP in state $s$ and year $t$. All specifications include state and year fixed effects. Standard errors are clustered at the state level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

| | Ln(Establishment Entry by All Firms) | | | Ln(Establishment Exit by All Firms) | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| $D_{s,t}$ | -0.148* | -0.160** | -0.157** | -0.230** | -0.237** | -0.237** | -0.229* | -0.238** | -0.239** |
| | (0.075) | (0.070) | (0.077) | (0.115) | (0.105) | (0.105) | (0.120) | (0.110) | (0.112) |
| $Ln(NLoanLess1MRev_{pretreatment}) * D_{s,t}$ | 0.016** | 0.010 | 0.002 | -0.005 | -0.008 | -0.007 | | | |
| | (0.007) | (0.007) | (0.005) | (0.011) | (0.011) | (0.015) | | | |
| $Ln(NLoanLEQ1M_{pretreatment}) * D_{s,t}$ | | | | | | | -0.004 | -0.007 | -0.006 |
| | | | | | | | (0.010) | (0.011) | (0.014) |
| $Ln(Pop_{s,t})$ | | 1.114*** | 0.744*** | | 0.615 | 0.638* | | 0.608 | 0.635* |
| | | (0.177) | (0.260) | | (0.405) | (0.371) | | (0.401) | (0.371) |
| $Ln(Pop_{s,t})$ | | | 0.300** | | | -0.019 | | | -0.022 |
| | | | (0.140) | | | (0.248) | | | (0.249) |
| Constant | 8.924*** | -7.902*** | -5.921** | 9.152*** | -0.133 | -0.259 | 9.152*** | -0.034 | -0.183 |
| | (0.008) | (2.673) | (2.871) | (0.012) | (6.123) | (5.539) | (0.012) | (6.067) | (5.480) |
| Observations | 561 | 561 | 561 | 561 | 561 | 561 | 561 | 561 | 561 |
| R-squared | 0.320 | 0.462 | 0.497 | 0.739 | 0.750 | 0.750 | 0.739 | 0.750 | 0.750 |
| Number of States/Territories | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Clustered SE (State Level) | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

**Table 1.14. Regulation CF and Business Dynamics (Small Businesses)**

This table reports the differences-in-differences estimates of the effect of Regulation CF on establishment exit by small businesses conditional on the pre-treatment measures of local financial market development. The dependent variable is the log of establishment exits by firms with fewer than 20 employees. The observations are at the state-year level, and the sample period is 2009 to 2019. $D_{s,t}$ is an indicator equaling one from 2016 onward for all states. $Ln(NLoanLEQ1M_{pretreatment})$ is log number of loans with origination amounts less than or equal to \$1 million and $Ln(NLoanLess1MRev_{pretreatment})$ is log number of loans to businesses with revenue less than or equal to \$1 million in 2015 (the year before the passage of Regulation CF). $Ln(Pop_{s,t})$ is log of population and $Ln(GDP_{s,t})$ is log of GDP in state $s$ and year $t$. All specifications include state and year fixed effects. Standard errors are clustered at the state level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

| | Ln(Establishment Exits by Firms with fewer than 20 Employees ) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $D_{s,t}$ | -0.223* | -0.234** | -0.234* | -0.225* | -0.233** | -0.233** |
| | (0.132) | (0.116) | (0.119) | (0.125) | (0.110) | (0.111) |
| $Ln(NLoanLEQ1M_{pretreatment}) * D_{s,t}$ | -0.003 | -0.006 | -0.006 | | | |
| | (0.012) | (0.011) | (0.015) | | | |
| $Ln(NLoanLess1MRev_{pretreatment}) * D_{s,t}$ | | | | -0.003 | -0.007 | -0.007 |
| | | | | (0.012) | (0.011) | (0.015) |
| $Ln(Pop_{s,t})$ | | 0.747* | 0.749* | | 0.753* | 0.752* |
| | | (0.440) | (0.419) | | (0.444) | (0.420) |
| $Ln(GDP_{s,t})$ | | | -0.002 | | | 0.001 |
| | | | (0.255) | | | (0.255) |
| Constant | 8.961*** | -2.326 | -2.337 | 8.961*** | -2.414 | -2.409 |
| | (0.013) | (6.656) | (6.126) | (0.013) | (6.716) | (6.188) |
| Observations | 561 | 561 | 561 | 561 | 561 | 561 |
| R-squared | 0.742 | 0.757 | 0.757 | 0.742 | 0.757 | 0.757 |
| Number of States/Territories | 51 | 51 | 51 | 51 | 51 | 51 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Clustered SE (State Level) | Yes | Yes | Yes | Yes | Yes | Yes |

**Table 1.15. Regulation CF and Business Dynamics (Young Employer Firms)**

This table reports the differences-in-differences estimates of the effect of Regulation CF on establishment entry and exit of young employer businesses conditional on a pre-treatment measure of local financial market development. The dependent variable in columns (1) to (3) is the log of establishment entry by firms that are still active one to five years after becoming employer businesses. The dependent variable in columns (4) to (6) is the log of establishment exit by firms that are still active one to five years after becoming employer businesses. The observations are at the state-year level, and the sample period is 2009 to 2019. $D_{s,t}$ is an indicator equaling one from 2016 onward for all states. $Ln(NLoanLEQ1M_{pretreatment})$ is log number of loans with origination amounts less than or equal to $1 million in 2015 (the year before the passage of Regulation CF). $Ln(Pop_{s,t})$ is log of population and $Ln(GDP_{s,t})$ is log of GDP in state $s$ and year $t$. All specifications include state and year fixed effects. Standard errors are clustered at the state level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

| | Ln(Establishment Entry by Firms with Age 1 to 5 years) | | | Ln(Establishment Exit by Firms with Age 1 to 5 years) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $D_{s,t}$ | -0.310** | -0.326*** | -0.321** | -0.464*** | -0.484*** | -0.476*** |
| | (0.144) | (0.122) | (0.125) | (0.167) | (0.131) | (0.141) |
| $Ln(NLoanLEQ1M_{pretreatment}) * D_{s,t}$ | 0.017 | 0.012 | 0.008 | 0.005 | -0.001 | -0.007 |
| | (0.012) | (0.012) | (0.012) | (0.014) | (0.013) | (0.018) |
| $Ln(Pop_{s,t})$ | | 1.086** | 0.912* | | 1.284** | 1.026* |
| | | (0.430) | (0.489) | | (0.613) | (0.554) |
| $Ln(GDP_{s,t})$ | | | 0.140 | | | 0.207 |
| | | | (0.192) | | | (0.301) |
| Constant | 6.347*** | -10.064 | -9.111 | 8.323*** | -11.081 | -9.673 |
| | (0.014) | (6.497) | (6.636) | (0.018) | (9.267) | (8.446) |
| Observations | 561 | 561 | 561 | 561 | 561 | 561 |
| R-squared | 0.688 | 0.705 | 0.706 | 0.792 | 0.811 | 0.813 |
| Number of States/Territories | 51 | 51 | 51 | 51 | 51 | 51 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Clustered SE (State Level) | Yes | Yes | Yes | Yes | Yes | Yes |

# Chapter 2. From In-person to Online: the New Shape of the VC Industry

*This chapter is coauthored with Liudmila Alekseeva[1], Silvia Dalla Fontana[2], and Caroline Genc.[3]*

## 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*

Active involvement with their investments sets venture capital (VC) investors apart from the typical financial intermediary. These investors not only provide startups capital but also support them through multiple post-investment services (Gorman and Sahlman, 1989; Lerner, 1995; Hellmann and Puri, 2002; Gompers et al., 2020). Because VC investors 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 (Petersen and Rajan, 2002). Therefore, in-person interactions have been perceived as crucial in the VC industry both for the selection process and post-investment activities (Bernstein et al., 2016). In fact, to accumulate and exchange soft information, VCs spend much of their time networking (Gompers 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 by studying the consequences of a restriction on such interactions. In this paper, we exploit the sudden interruption of in-person communication due to the recent pandemic to explore changes in VC investing


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when all face-to-face communication is replaced by online meetings. Even though online interactions might be a good substitute for in-person ones, they seem imperfect. Roelof Botha, a VC at Sequoia Capital, one of the largest VC firms in the United States, recently 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*"[4]. Thus, we describe changes in VCs' behaviors around an event that stressed the traditional norms of the VC industry.

Using Pitchbook data on VC investments in the United States, we provide evidence on how a change in soft information collection from in-person to online impacted the behavior of these active financial intermediaries. We start by investigating whether the geography of the VC investments is transformed with the arrival of the Covid-19 outbreak. As it is more difficult and costly to communicate with distant parties, distance has been perceived as an important barrier to soft information collection (Petersen and Rajan, 2002; Agarwal and Hauswald, 2010). Since the pandemic-related restrictions forced investors to interact with all firms in the same way, i.e., online, the gap in the quality of soft information and the cost of its collection between proximate and distant companies was reduced. Therefore, we can expect VCs to break their traditional investment model and invest in more distant startups. Also, by replacing face-to-face interactions with online meetings, the pandemic might have changed the type of soft information that VCs can collect about early-stage companies[5]. Thus, we explore if changes in interactions and information collection lead VC investors to revise their requirements about their portfolio companies' characteristics and to adjust their syndicate's structure.

We first focus on the distance between VC investors and their portfolio companies. One main consequence of the new environment imposed by Covid-19 is that physical distance has become less constraining since all firms, whether very close to each other or not, were forced to interact similarly: online. As soft information collection was no longer facilitated by proximity, we expect the distance between VC investors and their portfolio companies to increase post-pandemic. Since distance between financial intermediaries and small businesses has been on a decades-long increasing trend (Petersen and Rajan, 2002), we check for the existence of an increasing secular trend in distance for VCs as well. Therefore, we expect that the pandemic significantly accelerated an already existing trend. This is exactly what we observe from our first set of results. We document a steady increase in distance between investors and portfolio companies since the beginning of our data. However, even after controlling for the existing trend, we document a post-Covid increase in distance between a VC firm and its portfolio company of 35% in a cross-section of all VC first-round investments. When looking at the variation within a VC firm, we still observe a distance increase of 21%. Our findings

[4]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.

[5]VCs respond strongly to information about the founding team (Bernstein et al., 2017) and make investment decisions based on gut feelings and personal bonds with entrepreneurs (Hu and Ma, 2021; Gompers et al., 2020).

suggest that this increase in distance also translates into VCs being more likely to invest outside their state borders: VCs are nearly 13% less likely to invest in their own state. We additionally document that this distance growth reflects some redistribution of the number of VC investments from large entrepreneurial hubs (i.e., San Francisco, San Jose, Oakland, Boston, Cambridge, or New York) toward non-hub areas. VCs located in hubs are less likely to invest in hub companies after Covid, while VCs located outside hubs are equally likely to invest in hubs before and after.

To pin down the mechanism underlying our results as much as possible, we supplement our analysis by testing the heterogeneity in distance increase depending on the Covid-related restrictions and the severity of Covid shock in the states of VCs location. Even though the variation in pandemic-related restrictions across U.S. states is rather limited[6], results of this analysis might indicate whether our proposed mechanism is plausible. 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. Our results consistently support this hypothesis. We also find evidence consistent with VCs making more careful steps when the collection of extensive soft information or on-site visits are limited. The distance to investment increases more for smaller deals than for large ones, and the distance increases less for startups from capital-intensive industries that might require more substantial information to make the investment decision.

One more relevant fact to consider is that Covid-19 not only transformed the way firms do business but also significantly impacted the economy overall. This is why in our analysis, we try to exclude the explanation that VCs invest in distant states because these areas house industries that suffered less or even benefited from the pandemic. In that case, the increase in distance would only be a consequence of a higher focus on specific states because of their post-pandemic economic growth. To refute this explanation, we control for the change in states' growth rates, and we do not find evidence supporting this alternative explanation. We finally exclude the possibility that VCs invest farther away due to the high amount of capital they have on hand by controlling for the total amount of capital raised by VC funds at the analyzed investor's location in all distance-related regressions.

Our findings regarding distance 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 VCs' investment characteristics. If in-person interactions are not essential to acquire

[6] Most U.S. states introduced Covid-19-related restrictions in March 2020. See Section 2.5.2 for more details.

soft information or if online communication provides a perfect substitute for in-person meetings for such information collection, we should not observe significant differences before and after Covid. On the contrary, if online communications cannot fully replace in-person interactions, we should observe significant changes in the types of investments VCs select and in the way they structure deals. Thus, we first consider company characteristics that can proxy for the need to obtain less extensive soft information, such as whether the startup comes from the VC's focus industry and whether it operated in a business that is similar to previously VC-financed startups. Our findings confirm that, in this new information environment, VCs are more likely to rely on their own industry expertise and select investments that are more familiar to them.

We then investigate if VCs change the way they invest in syndicates as a balancing mechanism to the change in their information environment. Syndication not only helps share risk but also enables VCs to bring together more expertise and insights on investment opportunities (Lerner, 1994). On the one hand, we expect VCs to reach out to other funds more in a period with lower availability of information and overall higher uncertainty. On the other hand, it might also be more difficult for them to get in touch during the pandemic and discuss co-investment opportunities than before. Even though VCs traditionally invest with other VCs and build larger syndicates when they invest in more distant startups (Sorenson and Stuart, 2001), we find that post-pandemic, this is no longer the case. This might reflect an increased difficulty of the syndicates' formation in a post-pandemic world. At the same time, we also observe that the average distance across syndicate members increases, as does the probability of investing with known syndicate partners. Besides, a syndicate is more likely to have at least one VC specialized in the company's industry. These results are coherent with a post-pandemic information environment becoming more challenging and with VCs leveraging their own network in a crisis.

Lastly, we provide some early insights into the performance of VC investments that were deal-sourced online rather than in-person. Due to the limited time that passed since the start of the pandemic, we first focus on the probability of raising a second financing round as a primary performance indicator. Our preliminary findings reveal that the probability of getting a second round within 12 or 18 months is higher for companies that received their first VC financing during the post-Covid period compared to those funded before. We then focus on the probabilities of companies to go public or to get acquired within 18 months since their first VC investment. Our exit-related results show that so far, companies that received their first VC round after Covid are slightly more likely to exit fast - within 18 months - mainly due to exits via M&A. Due to the very short time available to observe exits or second-round data for companies that received VC financing post Covid, these results should be interpreted with caution. Further explorations of data covering a more extended post-Covid period will enable us to shed light on how critical in-person interactions are for the performance of VCs' deal sourcing and post-investment activities. This, in turn, could indicate whether the traditional VC due diligence model based on in-person interactions delivered better quality investments than remote investing.

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; Liberti and Petersen, 2018). We attempt to provide an early performance analysis to assess how crucial soft information collected in person is for the VC industry. We also contribute to understanding how VCs adapt their selection and syndication processes when broadening their horizons in an unfamiliar environment, where access to the soft information they used to collect is constrained. Indeed, our results suggest that while VCs do not try to compensate for the inability of in-person due diligence by relying more on potential "hard information", they reduce their risk by relying more on their expertise and networks. Our study also adds to the literature on the geography of the VC industry (e.g., Sorenson and Stuart, 2001; Bengtsson and Ravid, 2009; Chen et al., 2010a; Cumming and Dai, 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 of in-person activities during the Covid-19 pandemic accelerated this change. Our findings show a sharp increase in distance between investors and their portfolio companies that does not revert back even after the restrictions on in-person interactions are removed. Finally, by analyzing the change in the VCs' behavior around the unexpected arrival of the pandemic, 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; Gompers et al., 2021).

Our results have a range of important implications. First, switching from in-person to online communication seems to induce VCs to reconsider the need for strong geographical clustering with their portfolio companies. This finding has potential implications for the diffusion of entrepreneurial activity and innovation spillovers outside traditional hubs. As VCs expand the geography of their investments, the importance of traditional clusters of innovative entrepreneurship might decrease, allowing for the growth of new hubs and the diffusion of valuable human capital. Second, we observe that their investment behavior seems to leverage their existing knowledge by investing in industries and businesses similar to the ones they were exposed in the past. Thus, VCs seem to be more cautious when choosing companies for online investment, even if they are located nearby. This result suggests that online interactions might not allow VCs to collect soft information that they used to collect via in-person networking. Finally, we observe that VCs seem to leverage their networks more than before. They co-invest in smaller syndicates, but with investors they know already from before. VCs reach out to more remote but trusted prior partners, and they include an industry expert in the syndicate. 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, these adjustment mechanisms suggest that even with evolving information technologies, it is impossible to perfectly replace soft information through online communication and that the VCs' behavior is sticky.

Thus, we should not expect soon dramatic changes in this industry, such as investments in rural areas or in substantially different startup characteristics.

The remainder of the paper is organized as follows: after reviewing the related literature in Section 2.2, we describe the data in Section 2.3, while Section 2.4 exposes our estimation strategy. Section 2.5 examines the new geographical scope of the VC industry and Section 2.6 details changes in investment characteristics and syndication process. We provide preliminary insights on performance in Section 2.7 before concluding with Section 2.8.

### 2.2 Literature Review

Our paper first contributes to the literature analyzing the role of soft information in financing decisions (e.g., Petersen and Rajan, 2002; Stein, 2002; Liberti and Petersen, 2018; Giroud, 2013). The need to rely on soft information is not unique to the VC industry; indeed, it is typical to all industries characterized by the lack of hard information. The VC setting is particularly well suited to study this area, as soft information is quite important in less hierarchical organizations (Stein, 2002; Berger et al., 2005), which is the case of VCs and startups. In a recent review of the literature,

By showing an increased willingness of VCs to invest in distant companies, our paper also adds to the literature on the geography of the VC industry and, in general, of all industries that particularly need to rely on soft information for their financing decisions. Until the Covid-19 onset, VCs were believed to be geographically concentrated and to invest in companies close to their headquarters (Sorenson and Stuart, 2001; Bengtsson and Ravid, 2009; Chen et al., 2010a; Cumming and Dai, 2010). We show that the need to move to online meetings changed the geographic shape of VCs' investments, and we try to understand the underlying mechanisms and consequences of such a change. As stated by

Also, the geographic concentration of VCs is not random at all.

The literature provides further evidence about the peculiarities of distant investments that we also analyze under the Covid-19 context.

Because we exploit the setting in which interactions were not entirely eliminated but forcefully transferred to the online world, we also speak to the literature analyzing the role of information technologies for collaboration. By reducing communication costs, the adoption of the Internet[7] played an essential role in new collaborations. In academia, for instance, it positively affected the productivity and the expansion of collaborative networks (Agrawal and Goldfarb, 2008; Ding et al., 2010). Moreover, these studies highlight the "equalizing force" of IT with a more pronounced effect on middle-tier universities, women, and scientists from non-elite institutions. Nevertheless, there is no consensus about the geographical shape of collabora-

[7]Most of the studies focus on BITNET, an early version of the Internet.

tions even though it is well established that the Internet reduced the importance of distance (Forman et al., 2005).

Finally, our paper contributes to the rich literature on the Covid-19 pandemic while being specific to venture capital and entrepreneurship research.

### 2.3 Data

In this paper, we use Pitchbook to obtain information on VC investments, given that it is considered one of the most comprehensive data sources about VC investment rounds[8]. It provides detailed information on deal characteristics, investors, and portfolio companies. For our analysis, we concentrate on investment rounds conducted by U.S.-based venture capital firms. To restrict our focus to venture capital deals, we first keep in our dataset investors whose *Primary Investor Type* is either "Venture Capital", "Corporate Venture Capital" or "Accelerator/Incubator". 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 United States: 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.

**[See Table ??]**

Table 2.1 presents descriptive statistics for the key variables used in the analysis. Panel A contains deal characteristics at the investor-startup level, and Panel B describes company characteristics at the unique company level. From Panel A, we observe that the average deal concerns an investor which is 1,318 km away from the portfolio company and which is located in the same state as the target company with a probability of 50%. The average deal in our sample involves almost four VCs per round, and 64% of the deals represent

[8] A previous version of this paper was written using Refinitiv data for the main analysis and included limited analysis with the use of Pitchbook. 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, we note that our results show qualitatively the same results with both Refinitiv and Pitchbook datasets.

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

a seed stage. Panel B shows that almost 40% of the target companies are located in California, and they are, on average, 3 years old at the time of receiving the analyzed investment[10].

**[See Table 2.1]**

We supplement our VC investment data in several ways. Using Refinitiv, we obtain VC fundraising data for U.S.-based venture capital funds to estimate a control for the VC capital available for investment at the state level. Table A2 provides an analysis of the long-term relationship between total VC funds' inflows to the state and the average distance to portfolio companies for VCs in this state. As the relationship between fundraising and distance is positive and significant, we include this variable in all our analyses to control for changes in the VC fundraising environment. To study the potential effects of new businesses and industry changes due to the Covid-19 crisis, we use Compustat and the monthly Business Formation Statistics (BFS) introduced by the Census Bureau to provide granular, timely, and high-frequency information about the pandemic and its effect on the U.S. states' economy [11].

**[See Table A2]**

### 2.4 Estimation Strategy

#### 2.4.1 Distance Analysis

In financial relationships involving small and opaque businesses (small business lending, venture capital, and real estate), soft information plays a key role because hard information is often unavailable. Therefore, in-person interactions are crucial as they constitute an essential source of soft information collection. Since it is more difficult and costly to communicate with distant partners, distance is perceived as an important barrier 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 collection and transmission of information changed.

[10]The company age is defined as one plus the difference between the deal year and the founding year of the company.

[11]The *BFS* provides business applications and formation time series at the national, state, and even industry level. The number of applications is obtained from the Internal Revenue Service (IRS) data based on Employer Identification Number (EIN) applications. Considering the importance of following fast-changing economic conditions, the Census Bureau made available weekly (starting from April 2020) and monthly data (starting from January 2021). Also, since the application process is mainly online and automated, new applications are processed almost immediately. Therefore, we use the monthly BFS data to construct different state-level measures. We use seasonally adjusted high propensity business applications (HBA) series to create our measures, as it captures the likelihood to become an employer business (specific conditions based on industry, type of entity, the reason for application, and wage are used to identify a high propensity business application).

Online communications increased the availability of timely hard information and reduced the use of soft information in lending relationships. As a result, the distance between small firms and their lenders has been increasing for decades (Petersen and Rajan, 2002). Although the VC industry wasn't exempt from this trend, it is one of the industries where geographical clustering still remains strong: where hard information is lacking, face-to-face and informal meetings are a norm that is difficult to change.

However, the Covid-19 pandemic created a strong unexpected stress on this norm by impacting the way people communicate. It interrupted all in-person meetings and introduced a widespread adoption of teleworking. Within March 2020, U.S. states' governments introduced 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 home. By the end of March, all U.S. states had introduced rather strict distancing measures, and everyone who could, started working from home. Thus, 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 other similar software can be observed in the soaring stock prices of their providers, reflecting how crucial web conferencing has become.[12] One main consequence of such severe restrictions on movement and communication is that physical distance has become less relevant. All firms, whether very close to each other or not, were forced to interact in the same way: online.

Before the Covid-19 onset, soft information about proximate companies was more accessible compared to distant companies. VCs used to organize different events to meet founders and other investors to learn more about existing and potential investments. As distance is traditionally considered a major barrier to soft information exchange, the VC industry is characterized by high geographical clustering that persists even to date, while the large availability of IT communication significantly impacted other financial intermediaries such as banks. After the pandemic outbreak, proximity provided no more advantage for information collection. Hence, it reduced the gap in the quality of soft information and the cost of its collection between proximate and distant startups. We expect that, in such conditions, VCs would break the traditional norm and expand their investment horizons, looking for promising investments beyond the usual borders. To explore whether the average distance to portfolio companies changed in response to the restrictions on in-person interactions, we use the following specification:

$$Distance_{j,i,t} = \beta_1 Post\ Covid_t + \beta_2 Time\ Trend_t + X'\theta + \alpha_i + \omega_m + \gamma_s + \eta_v + \epsilon_{i,j,t} \tag{2.1}$$

The dependent variable is the logarithm of one plus the distance measured in kilometers between investor $i$ and company $j$ at time $t$. We use the latitude and longitude of investors' and companies' zipcodes to estimate distance between them. The main explanatory variable, *Post Covid* is a dummy that equals 1 if

[12]For example, Zoom stock price grew from around \$100 in February 2020, to nearly \$560 in December 2020.

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, the natural logarithm of the total capital raised by VC funds in the VC's state lagged by one year[13], and a dummy variable for whether the company is located in an entrepreneurship hub. As distance has been increasing over the past decades as a consequence of advances in storage technology and computing (Petersen and Rajan, 2002), in all our specifications, we include a variable *Time Trend* to correct for the growth in distance between investors and portfolio companies that started before Covid[14]. The specifications also include the company's industry ($\alpha_i$) fixed effects, investment stage fixed effects ($\gamma_s$), VC investor fixed effects ($\eta_v$) as well as month ($\omega_m$) fixed effects to control for the seasonality of VC investments.

### 2.4.2 Investment Characteristics Analysis

To better understand how the restrictions on in-person communication affected VCs' selection process and investment strategies, we analyze changes in the VCs' investment characteristics. We first focus on how VCs adapt to the change in information environment by analyzing whether they adjust their selection criteria towards company characteristics that could proxy for the potential availability of hard information about the startup, such as its age and whether it previously obtained pre-VC financing. We also consider company characteristics that could proxy for the need to obtain extensive soft information and visit the startup in-person to make the investment decision, such as whether the startup comes from the VC focus industry, whether it offers a novel product or a product similar to previously VC-financed startups, and whether it comes from a knowledge- and capital-intensive industry. We then explore at the VC level 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 (Sorenson and Stuart, 2001). We also examine if VCs balance investment risks by creating syndicates with previously known syndicate partners and including industry experts in syndicates. In the final part of this analysis, we investigate changes in attributes that are more closely linked to the bargaining power of investors.

In general, on the one hand, if online and in-person interactions prove to be perfect substitutes, then we should see no significant change in the VC's investment selection behavior. On the other hand, we can expect VCs to adjust their investment selection criteria and syndicates formation processes post-pandemic to compensate for the difficulty to obtain soft information, if online and in-person interactions are not perfect substitutes. The following regression specification is used to analyze investment characteristics in

[13]We control for VC capital raised to ensure that the change in distance is not driven by competition between VC firms and increased capital chasing limited local investment opportunities. See section 2.5.5 for further explanations.

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

the post-pandemic period:

$$\begin{aligned} Investment\ Characteristic_{j,i,t} = & \beta_1 Post\ Covid_t + \beta_2 Time\ Trend_t \\ & + X'\theta + \alpha_i + \omega_m + \gamma_s + \eta_v + \epsilon_{i,j,t} \end{aligned} \tag{2.2}$$

where the dependent variable takes the form of various characteristics of investment made by investor $i$ in company $j$ at time $t$. The main explanatory variable in this equation is $Post\ Covid_t$, where as before, it is a dummy that equals 1 if the financing round happened after February 2020, and zero otherwise. Control variables and fixed effects are defined as in equation 2.1. We also make sure to control for the linear time trend in these investment characteristics regressions.

## 2.5 Investing Across Usual Borders: the New Shape of the VC Industry

While VC investors highly value face-to-face interactions due to the lack of tangible information about the quality of young startups, the Covid-19 onset interrupted this routine. Startup demos, networking events, and dinners with founders were no longer possible with the arrival of the pandemic. VCs had to adopt videoconferencing as the primary tool to keep learning about investment opportunities, meet startup founders, and monitor portfolio companies. Collecting information about a neighboring startup became as complicated as collecting information about a startup located a thousand miles away. Therefore, we expect that the leveling out of communication with proximate and distant partners led VCs to expand their geographical investment horizons. When there is no benefit in focusing on local startups, a new investment opportunity from far away becomes at least as attractive.

### 2.5.1 Main Results

Our results support the idea that the leveling out of communication costs with proximate and distant startups made investment opportunities located far away at least as attractive 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 average increase in distance between economic agents, such as lenders and borrowers, started decades before the Covid-19 pandemic. In fact, 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 exhibits a clear jump in the average distance in 2020 and suggests the acceleration of the distance growth trend after the pandemic, with Covid fueling distant investments. We also notice an overall persistence of this post-Covid effect and no mean reversion, with just a slight decrease in the average distance in March-July of 2022 (represented by the last value in the graph) compared to 2021.

**[See Figure 2.1]**

Table 2.2 further confirms these observations by reporting the results of our main regression specification described by equation 2.1. In all the specifications, the coefficient of *Post Covid* is positive and significant at the level of 1%, suggesting that the post-pandemic average distance between VC investors and their portfolio companies increased substantially even when adjusting for the secular trend in distance increase, *Time Trend*. In a cross-section of all VC investments (column (1)), the coefficient of *Post Covid* is 0.303, suggesting that the distance between a VC firm and its portfolio company increased on average by 35% after the pandemic. If we focus on the distance "within" a VC investor's portfolio (column (2)), the increase attributed to the Covid-19 is about 21%. Finally, when we additionally control for whether the portfolio company is located in an entrepreneurial hub [15], the increase in distance post-Covid is still substantial: 19%. Figure 2.2 complements these results by showing how important the changes are in terms of distance range. We can observe that VCs perform relatively fewer deals within a short distance to their headquarters (within 50 km), but perform significantly more deals in very far locations (more than 1,000 km away).

**[See Figure 2.2]**

**[See Table 2.2]**

Next, we test if VCs invest within their own state or if they also became more likely to invest across geographical borders. Table 2.2 underlines that VCs are 3.1 to 6.5 percentage points less likely to invest inside their state (columns (4) and (5)). This represents a 6-13% decrease in the unconditional probability of own-state investments due to the pandemic.

The map in Figure 2.3 additionally illustrates the extent to which VCs expand their geographical horizons after the pandemic. It shows 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

[15] Unreported coefficient of the dummy variable for whether the company is located in San-Francisco, San Jose, Oakland, Cambridge, Boston, or New York is negative and strongly significant

for VCs). Light blue-colored counties are places that have been obtaining VC financing since the pre-Covid period (already familiar places for 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.

**[See Figure 2.3]**

To confirm our distance-related finding, we further investigate distances between the startup and its most proximate VC investor as well as its most remote investor. Columns (1) to (3) of Table 2.3 show that the minimum distance between a startup and its VCs increases substantially more post-Covid than it would have increased otherwise (due to *Time Trend*). The magnitude of the coefficients varies between 25 and 29% when including VC fixed effects (columns (2) and (3)), while it is around 33% in the cross-sectional specification (column (1)). This finding suggests that the pandemic contributed to making even the closest investors significantly more distant. Unsurprisingly, columns (4) to (6) in Table 2.3 confirm our baseline result about distant investments. They reveal that the distance between a startup and its most remote investor increases by more than 26% due to the Covid onset.

**[See Table 2.3]**

Our findings are also robust to several other tests reported in the Appendix. Table A4 shows results similar to Table 2.2 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. Results are also robust to excluding VC deals made by investors defined as "accelerators" and "CVCs", as reported in Table A5. Focusing on deals from Lead VC investors only does not change our findings either (see Table A6). We also test the robustness of our results to changes in the start date of the pre-Covid period and to control for the pre-trend and the post-trend separately. Table A3 shows that while the average distance (the probability of investing in the same state) was increasing (decreasing) before Covid, this trend becomes much stronger in the post-Covid period, irrespective of when we consider the start point of the pre-trend.

**[See Table A3]**

**[See Table A4]**

**[See Table A5]**

**[See Table A6]**

### 2.5.2 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.

We obtain data for this analysis using the Oxford COVID-19 Government Response Tracker (Hale et al., 2021). Table **??** summarizes the average restrictions 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 rather limited, especially among the three states originating the largest number of deals: California, New York, and Massachusetts[16]. Nevertheless, we repeat our distance analysis by substituting *Post Covid* variable with a VC's state-level measure of restrictions Stringency Index, the natural logarithm of the total number of Covid cases, and the natural logarithm of total Covid-related deaths, measured as monthly averages of respective daily indicators reported by the COVID-19 Government Response Tracker. The continuous nature of these measures allows us to additionally introduce year-month fixed effects instead of a linear time trend in the regressions and therefore explore the variation across states 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 period after the pandemic onset, while the pre-pandemic data helps to estimate other regression parameters.

Table 2.4 shows the results of this analysis. The regressions include year-month and VC state fixed effects (VC state replaced by VC investor fixed effects in columns (4) to (6)) in addition to our usual set of controls and fixed effects. In the regressions with VC state fixed effects, the coefficient of *Stringency Index* is statistically insignificant, suggesting that there is no significant correlation between the stringency of the lockdown measures in the VC's state and the distance to investments. However, as mentioned above, the variation of this and related indices across states in the COVID-19 Government Response Tracker is limited.

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

Therefore, the lack of a significant relationship might stem from the lack of statistical power. When we proxy the severity of the Covid shock and the propensity to choose online communication rather than in-person with the number of Covid cases and Covid-related deaths, the coefficients are positive and statistically significant. Thus, VCs located in states that were hit more severely by the pandemic tend to invest in more remotely located companies. *Ln(N Covid Cases)* coefficient magnitude suggests that with a 100% increase in Covid-related cases, VCs invest in companies 10% farther away. The coefficient for the number of deaths has a similar magnitude. Replacing VC state fixed effects with VC investor fixed effects generates similar but slightly larger magnitudes, with a positive coefficient of the Stringency Index becoming statistically significant at a 5% level. Overall, we observe a positive correlation between the severity of Covid-related restrictions and the health shock with the average distance to investments, supporting the view that the pandemic, indeed, was a strong facilitator of more remote VC investments.

**[See Table 2.4]**

### 2.5.3 Distance Increase Heterogeneity

Then, we ask whether this increase in distance is observable for all types of deals or whether there is some heterogeneity. We first focus on the deal size in Table 2.5. 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. Next, in Table 2.6, we study the post-Covid change in the distance by industry. We anticipate the distance to increase less for capital-intensive industries that potentially require more soft information and an in-person visit to the business site to make the investment decision.

**[See Table 2.5]**

**[See Table 2.6]**

Table 2.5 reports the results of our main 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 both in the cross-section of all investments and within a lead VC firm, 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.

Regarding the industry analysis, Table 2.6 reveals that not all industries equally experience the increase in distance due to the pandemic[17]. Panel A reports cross-sectional results, while Panel B includes VC investor fixed effects. In Panel A, columns (1) to (4) show industries for which the distance increase is accelerated by the Covid-19: Software, Finance, B2B, and B2C. Columns (5) to (8) correspond to industries for which the coefficient of *Post Covid* is statistically insignificant, such as Pharmaceuticals & Biotechnology, Healthcare, Hardware, and Energy & Materials. For these industries, there is no acceleration of the existing trend (*Time Trend*), and the distance increase does not seem to be catalyzed by the pandemic. Indeed, at first glance, the industries that experienced the increase in distance due to the pandemic, especially the Software or Finance sector (73% of which are fintech companies), can be perceived as better suited to adapt online communications as the result of pandemic-driven interruption in face-to-face meetings since they are typically less capital-intensive and have a lower cost of experimentation (Ewens et al., 2018). Panel B further shows that when including VC firm fixed effects, among the first set of industries (columns (1) to (4)), only two sectors (Software and Finance) are concerned by the post-Covid increase in distance. The results of columns (5) to (8) are consistent with those of Panel A.

In a supplementary analysis, we explore what kind of VC investors drive this increase in distant investments. While one prediction can be that more experienced VCs might be reluctant to change their investment model, we also know that those VCs can be better equipped to invest in more distant companies because they have larger networks with other venture capital firms, entrepreneurs, and professional services providers in various locations (Sorenson and Stuart, 2001). We rerun our distance regressions, splitting the sample into three groups with respect to investor age. Table A8 in the Appendix shows that the coefficient of *Post Covid* is positive and statistically significant for medium and old VCs while it is insignificant for young

[17]We perform a slight adjustment to industry definitions provided by Pitchbook to form more intuitive groups of companies and to avoid keeping individual industries with very few observations. More specifically, we reclassify fintech companies from Pitchbook industry sector “IT" into industry sector “Financial Services" (“Finance" in the table), “Pharmaceuticals and Biotechnology" Pitchbook industry group into a separate industry from under “Healthcare" Pitchbook industry sector, “Computer Hardware" and “Semiconductors" from under “IT" sector into new “Hardware" industry, and combine “Energy" and “Materials and Resources" into one newly defined industry (“Energy & Materials"). Newly defined “Software" industry represents the remaining observations from the “IT" industry sector (after removing fintech, “Computer Hardware", and “Semiconductors"), “Healthcare" - remaining observations from the "Healthcare" Pitchbook sector (after removing “Pharmaceuticals and Biotechnology"), “B2B" and “B2C" correspond exactly to respective sectors defined by Pitchbook.

VCs. Thus, the increase in distance due to the pandemic seems to be primarily driven by more experienced VCs, in line with

**[See Table A8]**

### 2.5.4 Implications of Distance Increase

Does this increase in distance reflect the reallocation of VC investments from established entrepreneurial hubs towards other locations post-Covid? If participating in the typical in-hub activities such as networking events and informal gatherings had some value, we expect that post-pandemic, as companies located in an entrepreneurial hub could no longer benefit from this competitive advantage, the probability of selecting a portfolio company located in a hub is lower. We address this question by looking at the likelihood that the portfolio company is located in the state of California or one of the entrepreneurial hubs (i.e., San-Francisco, San Jose, Oakland, Boston, Cambridge, New York). Table 2.7 shows that in the cross-section, there is a statistically significant redistribution of the number of investments from CA and hubs toward other areas (columns (1) and (3)). Although this redistribution has already started before the pandemic (as indicated by the negative and significant *Time Trend* coefficient), the Covid-19 pandemic fostered it substantially. Due to Covid, a portfolio company is 4.7 percentage points less likely to be located in the state of California and 2 percentage points less likely to be in the entrepreneurial hub's metropolitan area. When we analyze investments with VC fixed effects, i.e., "within" VCs' portfolios, we can observe that once everything moved online, a VC investor is respectively 2.6 and 2.3 percentage points less likely to invest in a CA and hub-located company. These changes represent an almost 7% decrease in the unconditional probability of investing in a CA or hub-based company.

**[See Table 2.7]**

We next investigate whether VC firms located in and outside entrepreneurial hubs behave differently with respect to whether they choose companies located in or out of hubs. For this purpose, we split our sample based on the lead VC firm's location in or out of large entrepreneurial hubs. Table 2.8 shows that in-hub VC investors are those responsible for the pandemic-related decrease in the proportion of portfolio companies located in hubs. Lead VCs located outside the hubs do not seem to change their preference for in-hub or out-hub portfolio companies. Therefore, we might see evidence of the redistribution of the VC investments from hubs toward non-hub areas. This is consistent with

**[See Table 2.8]**

### 2.5.5 Alternative Explanations

While the expansion of web conferencing services due to the Covid-19 outbreak seems to be an intuitive contributor to the rise of distant investments, alternative explanations require some attention. This section examines whether the increase in distant investments is due to the emergence of new opportunities in areas far from VCs. Indeed, a state far away from the average VC may become attractive to investors for at least two reasons. First, the industry composition of a state may explain its attractiveness: VCs might be more inclined to invest in states that experience higher growth due to Covid-19 because they house many industries benefiting from the pandemic. If true, the increase in distance after Covid-19 will be fully explained by a faster state growth of more distant states. Second, a distant state may be appealing to investors if the fraction of new businesses located there is higher than before. If new businesses are created in states that are far away from the usual clusters, the new geographical distribution of potential investment opportunities may explain the increase in distant investments independently from the Covid-19 context.

#### Industry Change

Since the Covid-19 crisis impacted the overall economy, to conclude that VCs invest farther away due to the leveling up of the quality and the cost of information acquisition for proximate and distant companies, we first need to exclude that VCs are not investing in distant states due to a higher post-Covid preference for industries clustering in these states. If distant areas are more developed around industries that benefited from the pandemic, VCs might have preferred to invest there even without limitations on the acquisition of soft information. Thus, some states might be experiencing higher VC financing post-Covid since they are more specialized in industries that benefited from the pandemic.

To exclude this alternative explanation, in our regressions, we control for whether the portfolio company's state experienced an above-median change in its growth rate due to Covid-19 (i.e., it is a *High-Growth State*). We estimate the change in the state growth rate due to Covid-19 as the difference between its growth rates in 2020 and in pre-pandemic 2019. This enables us to determine the states that outperformed during the most severe Covid year. The state's growth rate is computed as the weighted average of growth rates in 3-digit NAICS industries. We use employment shares of industries in the state from Census' Business Patterns data as industry weights. Industry growth rates are estimated using Compustat data on listed firms' average market capitalization growth during 2019 and 2020. If this alternative explanation is at play, i.e. post-Covid state growth explains the increase in distance between VCs and their portfolio companies, the interaction between *Post Covid* and *High-Growth State* variable should be positive and significant while making the coefficient of *Post Covid* alone insignificant.

Table 2.9 shows whether the change in the state growth explains the observed increase in distance. Columns (2) and (3) focus on the relationship between distance and the change in the portfolio company's state growth. Those states that had a larger change in their growth rates due to Covid (*High-Growth State* dummy) do not seem to explain the growth of distance to investments since the coefficient is negative and significant in column (2). Even though column (3) reports a positive but insignificant coefficient for the interaction term *Post Covid* x *High-Growth State*, the individual *Post Covid* coefficient decreases only slightly and remains strongly statistically significant. This result suggests that the acceleration in the states' growth during 2020 does not fully explain the growth in distance post-Covid.

**[See Table 2.9]**

### New Business Creation

To understand if the growth of distant investments observed after the Covid-19 onset is due to changes in the location of new businesses, we focus on the evolution of business applications at the state level. The Business Formation Statistics (hereafter BFS) data reports the number of business applications per state for each month. This enables us to compute the average annual growth rate of business applications. Since High Propensity Business Applications (HBA) are better suited to measure potential employer businesses, we construct our variables based on seasonally adjusted HBA. Based on the HBA growth rates we define the variable *High-Growth State (HBA)* as equal to one if the state has an above-median change in the high propensity business applications growth rate. If such states correspond to states that are farther away from VCs, the increase observed in distant investments may be explained by the growth in new distant businesses, independently from the change in the soft information collection context. In this case, interacting *High-Growth State (HBA)* with our *Post Covid* dummy should reveal a positive and significant coefficient that captures all the significance of the *Post Covid* variable alone.

Columns (4) and (5) of Table 2.9 show that the growth in business applications is not driving our results. We do not observe a statistically significant coefficient when interacting *High-Growth State (HBA)* with *Post Covid* variable, while the individual *Post Covid* remains statistically significant. Interestingly, the magnitude of the individual *Post Covid* slightly decreases in column (5), suggesting that part of the distance increase might be explained by investing in states that experienced a sharp increase in HBA growth rates, but this is not the whole story.

**Additional Robustness Results**

Because the standard distance specification only allows us to observe the deals that were completed, we run an alternative robustness exercise implementing a state selection model by a VC investor. In this model a VC observes all states' growth rates in terms of industry and business applications growth during the most severe Covid year and decides how to redistribute its investments across states based on this information. More specifically, the data we analyse includes observations at the VC investor - U.S. state level. The dependent variable in this analysis is the change in the proportion of the VC's investments in a specific state between pre-Covid years (2013-2019) and post-Covid period (2020-2022). The main independent variable of interest is the natural logarithm of distance between the VC and the state (we use the average distance to actual investments when the VC invested in the state and we use the latitude and longitude of the state's geographical center to compute the distance between the VC and the state "on average" when VC had no investments in the state). Other explanatory variables include the change in the states' growth rates between 2019 and 2020, measured as described above.

Table A7 shows the results of this regression analysis. It indicates that, on average, VCs increase the proportion of deals in states that are located farther away from the VC's headquarters. If the increase in more remote deals is explained by VCs simply choosing the states that benefited from the pandemic, then the interaction of the distance between the VC and the state with *High-Growth State*$_i$ variable should be positive and significant, while eliminating the statistical significance of the individual distance coefficient. Indeed, we observe that the magnitude of the distance coefficient slightly decreases in columns (3) and (5) that include the interaction of distance with a dummy for *High-Growth State*$_i$ and *High-Growth State*$_i$ *(HBA)* respectively. Despite the fact that, indeed, VCs seem to invest in more remotely located states that experienced an above-median change in growth rates, this does not fully explain the increase in the share of investments in more distant locations. The results of this selection-style model are therefore consistent with our baseline regressions controlling for the state growth in Table 2.9.

**[See Table A7]**

**[See Table 2.9]**

### Venture Capital Activity

The last couple of years were also characterized by a boom in venture investing[18]. 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. Therefore, an alternative explanation to our findings might be that the increase in distance is related not to a change in the information collection process but to a higher local competition among VCs that makes them seek investments in more distant areas. To ensure that the change in distance to investments and in other deal characteristics is not driven by too much money chasing limited local investment opportunities, we use VC fund inflows to the state of the analyzed VC lagged by one year as control. Table A2 shows the 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). The correlation between the average distance to portfolio companies and the one-year-lagged venture capital amount raised by funds in the state is positive. The coefficient is small in magnitude: a 1% increase in the state's VC funds' inflows is associated with a 0.03% larger distance between this state's VCs and their portfolio companies. Nevertheless, in all regressions, we control for this measure of local venture capital available for investment to ensure that the relationship with *Post Covid* is not related to the increase in VC funds' inflows observed during that period.

## 2.6 Investment Characteristics and Syndication

### 2.6.1 Changes in Investment Characteristics

In the previous section, we documented an increase in distance between VCs and their portfolio companies following the unexpected arrival of the Covid pandemic and resulting restrictions on in-person interactions. In the literature, it is established that soft information is critically important for investing in startups because of the high information asymmetry between VCs and entrepreneurs (e.g., Tian, 2011). It is also shown that, 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). If videoconferencing doesn't provide VCs with an adequate replacement for face-to-face meetings and monitoring, we can expect VCs to compensate by

[18]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

choosing less risky investment behaviors and by relying more on their own expertise. Thus, to understand whether and how VCs handle the pandemic-driven limited access to soft information, we first explore if they now leverage their own experience to judge investment opportunities in this new environment. We test if, post-Covid, they prefer to invest in companies from their focus industry and with businesses similar to previously VC-funded companies. Then, we investigate if they balance the lack of soft information with potential hard information by investing in older companies or companies with pre-VC financing.

The first aspect of VC deals we analyze is the likelihood of investing in the VC's focus industry. VC investors tend to specialize in a specific industry since it enables them to accumulate industry expertise and to build a strong network with founders and other professionals working in the sector. This helps them to collect valuable information about investment opportunities (Sorenson and Stuart, 2001). Therefore, investments made outside of the VC's focus industry may suggest risk-taking behavior or chasing hot opportunities (Sorenson and Stuart, 2008). We construct our industry focus variable based on the 40 industry groups classification from Pitchbook. We define the VC's focus industry as a broad industry in which the VC invested the largest amount by the year of the analyzed investment[19]. Table 2.10 shows that in the cross-section of deals in our sample, VCs are more likely to invest in companies from their focus industries after Covid (columns (1) and (2)). Moreover, these results remain when we add VC firm fixed effects, suggesting that, even within VC firms, there seems to be a preference to invest more in the focus industry after the Covid onset (columns (3) and (4)). Results in column (5) confirm this finding. This column shows the results of the regression in which the dependent variable is a dummy equal to one if at least one VC in the syndicate specializes in the portfolio company's industry. It reveals that, on average, a portfolio company might be more likely to have a VC focused on its industry after Covid, even though the coefficient is significant at the 5% level. Therefore, not only are VCs more likely to invest in their focus industry after Covid, but companies, in general, are more likely to be backed by a syndicate with at least one company's industry expert.

**[See Table 2.10]**

As this suggests a shift toward what can be seen as a more prudent behavior, in Table 2.11, we further investigate this suggestive evidence by looking at the similarity between start-ups selected before and after Covid. In this table, we compute the Jaccard Similarity score between two companies' keyword descriptions reported by Pitchbook. This enables us to obtain the average similarity of the company's product with

[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.

respect to other companies that received early-stage VC financing in the same industry sector during the last three years before the analyzed investment. In all specifications, the results show that 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 5-6% more similar to previously funded startups (the average similarity score in the sample is 2, which indicates that an average startup is 100% similar to 2% of same-industry startups funded in the past three years). This result is especially interesting in light of the fact that the pre-trend has a negative and significant coefficient, suggesting that before Covid VCs tried to invest in startups with increasingly more novel products. In a time of high uncertainty, investors seem to rely more on familiar businesses and select investments that might have a clear track record by the time of the analyzed deal.

**[See Table 2.11]**

As VCs might try to balance the limited access to soft information by selecting companies for which they can acquire other information, we next test if, post-Covid, VCs selected companies that are older or that have received earlier financing from accelerators, angels, crowdfunding platforms, etc. Table 2.12 reports the results of different variations of the regression equation 2.2 where the dependent variable is either the age of portfolio companies (columns (1) to (3)) or a dummy variable for having pre-VC financing (columns (4) to (6)). A pre-VC financing round is defined as a round categorized as “Accelerator/Incubator", “Equity Crowdfunding", “Product Crowdfunding", “Grant", or “Angel (individual)" and completed before the first VC financing. Considering their inability to benefit from in-person interactions as before, we expect VCs to rely more on companies' maturity and pre-VC financing to reduce their risk. Nevertheless, the overall results suggest that VCs do not necessarily rely on such characteristics that might convey more “hard information". We observe in columns (1)-(3) that, despite making more distant investments, VCs do not invest in more mature companies after Covid. Regarding the pre-VC financing-related results, we similarly observe that post-Covid, startups are not more likely to have a pre-VC financing round, while more remote companies are slightly more likely to have earlier financing (significant at 10% level). Notice that regression specifications from columns (4) to (6) additionally contain company age and pre-VC market activity[20]

**[See Table 2.12]**

[20]We control for the pre-VC market activity by including a natural logarithm of the total number of pre-VC deals lagged by two years to ensure that the results are not driven by the supply of pre-VC financing. We obtain similar results when we lag the control by one year.

The last startup-level characteristics we explore are pre-money valuation and the percentage of equity acquired by VCs in a deal. Investigating changes in pre-money valuations might help us better understand how the entrepreneurs' bargaining power changed after the Covid-19 onset. Table 2.13 reports the results of running regression equation 2.2 where the dependent variable is the natural logarithm of the startup's pre-money valuation. Given that during Covid-19 large amount of capital flowed to the private equity industry and a higher supply of capital may increase startups' valuations, as before, we control for the total capital raised by the VC funds in the investor's state lagged by one year. Since more mature companies might be more likely to have higher valuations, we also keep using company age control in this table. Panel A of Table 2.13 reports the results for the pre-money valuations change. In columns (1) to (4), the results reveal that there is no significant change in valuations post-Covid in the overall sample, with column (4) showing that normally the relationship between the distance to investments and pre-money valuation is also not significant. Motivated by earlier results about the redistribution of investments from the state of California towards other areas shown in Table 2.7, we repeat the analysis in the subsample of companies outside California. In this subsample, we find that pre-money valuations significantly increase post-Covid (by around 7%), suggesting a potentially higher competition for deals, consistent with relatively more deals being performed in these areas.

**[See Table 2.13]**

In Panel B of Table 2.13 we focus on the share of equity that is acquired by VCs in the deal. Overall, the results show that there is only weak evidence that VCs increase the share of acquired equity after Covid. The coefficient magnitude in columns (3) and (4) that include VC fixed effects suggest that investors acquire 0.7 percentage points more equity, or around 2.4% more relating to the unconditional mean. This result seems to be primarily driven by deals conducted in California, as the coefficient of *Post Covid* is insignificant in the subsample excluding such deals. Interestingly with the increase of distance to the company, the percent of acquired equity in general decreases.

### 2.6.2 Syndicate Formation

The geographical concentration of VCs is closely related to their pre- and post-investment activities: for VCs, identifying and evaluating opportunities is more straightforward when searching locally, as they invest in early-stage companies for which little information is available (Sorenson and Stuart, 2001). In addition, monitoring and adding value through other activities is also easier when the portfolio company is not far away (Bernstein et al., 2016). This is why investing in distant companies is more challenging, and networks/syndicates are key when investing farther away. 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 proximity became no more different than distance. As online interactions became the norm for everyone, finding investments or co-investors and learning about them became online activities. Therefore, 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; Lerner, 1994; Antweiler et al., 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 2.14, we test whether VCs are more or less likely to co-invest with other VCs after the pandemic onset. The results show that there is no significant change in the probability of syndicates formation in the post-Covid period. Columns (2) and (3) show that “within" a VC's portfolio, there is an increasing tendency to syndicate deals over time as indicated by the positive and significant *Time Trend* coefficient, which overall continued with the same tempo after the arrival of the pandemic: even though *Post Covid* coefficients are negative, they are not statistically significant. At the same time, results in columns (4) to (6) might indicate that the pandemic made syndicate formation more difficult. Even though VCs are not less likely to syndicate after Covid, the syndicates' size became 3-5% smaller. This is opposed to the overall long-term trend that shows a tendency for an increasing syndicate size.

**[See Table 2.14]**

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 an extension of 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 2.15 shows that distance among syndicate members increased significantly post-Covid. The dependent variable in the regressions is defined as a natural logarithm of the average distance (plus one) between a VC investor and other members of the same syndicate. Columns (1) to (3) add industry, state, and VC investor fixed effects one by one. In these specifications, the coefficient of *Post Covid* varies between 0.22 and 0.30, suggesting that the average distance between syndicate members increases by 25% to 35% after the Covid onset. This is a substantial increase compared to the average growth of distance between syndicate members over time captured by *Time Trend*. We then examine whether the distance between syndicate members varies with their distance to the portfolio company. Indeed, this increase in syndicate members' distance may be driven by the decision of the focal VC to make a distant investment. Column (4) shows that when the focal VC invests in a more remote company, the distance to its syndicate members, in fact, is larger. But the coefficient of *Post Covid* is still positive and statistically significant, even though somewhat smaller. Thus, the distance to the portfolio company does not fully explain the increase in syndicate members' distance Post Covid. This suggests that similar dynamics to those that drove the increase in distance between VCs and startups (i.e., the diminished advantage to communicate to proximate firms or co-investors, with respect to remote ones when every communication is online) might also play a role in the distance between VCs.

**[See Table 2.15]**

Syndicate partners become more geographically distant after the Covid onset, but 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 its partners in this syndicate. We are also interested to know how the propensity to partner with old syndicate members varies with the VCs' distance to the portfolio company.

Columns (1) and (3) from Table 2.16 show that VCs participate in syndicates with more old partners. The coefficient's magnitude suggests that the proportion of old syndicate partners increases by 3-4 percentage points, which translates into an approximately 12-14% increase in the old partners' share. Column (4) shows that this proportion slightly decreases with the distance to the portfolio company - the coefficient of *Ln(Distance+1)* is negative and significant. This might occur when a distant company invites its local VCs to the syndicate, which are less likely to come from the focal VC's local tighter network. Finally, it is interesting to point out that in the cross-sectional specifications in columns (1) and (2), we observe a negative *Time Trend* in the proportion of old partners. However, adding VC firm fixed effects changes the sign of the coefficient. Columns (3) and (4) show that, within the VC firm, the proportion of old partners in a syndicate has been increasing over time and is even higher after Covid. Therefore, the negative sign of *Time Trend* is driven by VCs that entered (or left) the market post-pandemic.

**[See Table 2.16]**

Lastly, we aim to clarify whether, for a specific VC, the likelihood to syndicate with partners located in the proximity of the portfolio company changes after Covid. Indeed, we might expect an increased propensity to make distant investments when there are VCs around the targeted company that can supervise it after the restrictions on in-person interactions are lifted. Table A10 shows that post-Covid, VCs invest with fewer other VCs located close to the startup, while we would have expected more partnerships with VCs nearby distant portfolio companies to alleviate information asymmetry. Specifically, the likelihood of having at least one VC within up to an hour drive (i.e., 50 km) from the portfolio company is lower post-Covid since the coefficients are negative and statistically significant in all columns. Therefore, the overall syndicate becomes more distant, and there are fewer VCs in the proximity of the portfolio company. These results are notably in contrast with the findings of

**[See Table A10]**

Overall, the results in this section suggest that VCs struggle to co-invest with more partners post-pandemic, but they also reach a more distant network while at the same time preferring to partner with their old connections. These results reflect the need to gather more information (more distant co-investors) and also the need 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.

## 2.7 Preliminary Insights on Performance

This last section provides some early insights from the investment performance side. Although we do not have long enough time post-Covid to properly assess the consequences of pandemic-related changes on the VC industry's performance, the question of whether online deal sourcing can be better or worse than the traditional one is important enough to have a preliminary analysis. As we only have 29 months of data since the beginning of the pandemic, which is a time period lower than the average time period for exits, we first focus on the probability of raising a second round as the most reliable intermediate outcome measure,[21] but still, additionally take a look at the likelihood of exiting via IPO or M&A within 18 months since the first VC financing. We analyze the probability of getting a second round within 12 and 18 months since the first VC financing.[22] For exits, due to the time needed to go public or to be acquired, we examine the associated probabilities only within 18 months.

When studying these probabilities, we use the same regression specifications as before, as in equation 2.2, where the dependent variable is a dummy for whether the company received a second round or not/exited or not. In exit regressions, on top of the usual controls and fixed effects used so far in the analysis, to ensure that specific market conditions do not drive our results, we follow Nahata (2008) and include a range of relevant controls. Specifically, we include the control for the VC fundraising in the investor's state in the year prior to the VC's first investment in the portfolio company as a measure of the VC capital inflows. Also, we include the median book-to-market ratio in the company's 3-digit NAICS industry, estimated based on public firms' data, in the year prior to the VC's first investment as a proxy for the VC investment environment[23]. Finally, we control for the IPO and M&A market conditions by including a measure of the lagged number of IPOs/M&A in the quarter before the completed exit; while for companies that still did not exit, it is equal to the average of the lagged quarterly number of IPO/M&A transactions over the entire analyzed time period after the first VC investment.

Table 2.17 reports results on the probability of receiving a second VC financing round. 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

[21] Hochberg et al. (2007) highlights that one-third of the companies in their sample do not survive the first round of financing and are thus written off.

[22] When considering the probability of getting a second round within a year (18 months), we need to drop companies that obtained financing less than in 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.

[23] We use a link between Pitchbook industries and SIC codes available for some companies to build a general crosswalk between Pitchbook industry definitions and 2-digit SIC codes.

funded before. Columns (4) to (6) suggest a similar conclusion for the probability of receiving a second round within 18 months. The coefficients magnitude implies that companies that received their first round after Covid, respectively, are around 9 and 11 percentage points, or almost 60% and 40% relative to the unconditional means, more likely to receive a follow-up round of financing, which is a significant increase in the probability. However, it is worth noticing that we lose a lot of observations because of the data truncation in the latter specifications. In general, results suggest that at least in these first months since the beginning of the pandemic, VCs are following up with further rounds of financing to companies sourced online not less than to those companies they decided to finance before the pandemic.

**[See Table 2.17]**

Columns (1) to (3) of table 2.18 report the results for the probability of going public or being acquired within 18 months. They show 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. Columns (4) to (6) and (7) to (9) separately report results for the likelihood of having an IPO and the probability to exit through M&A. The results reveal that exits via IPOs are not significantly more likely for companies that received VC financing post Covid: even though the coefficient is positive in the regressions, it is statistically significant at 10% in only one specification. At the same time, columns (7) to (9) show that the probability of M&A exit on average is higher: the coefficient of *Post Covid* is positive and strongly statistically significant.

**[See Table 2.18]**

Thus, these preliminary findings do not exclude the possibility that companies financed after the Covid-19 pandemic perform similarly or better in terms of fast exits compared to those funded before Covid. Further explorations of a longer time period would enable us to support or reject these early results.

## 2.8 Conclusion

VC investors highly value in-person interactions to make investment decisions. They are used to meet startup founders and other investors through frequent events to collect information about existing and new opportunities. Being actively involved, their post-investment activities also require close monitoring of their portfolio companies. Academic literature has shown that VCs' on-site engagement contributes significantly to their portfolio companies' success (Bernstein et al., 2016; Gompers et al., 2020). Thus, in-person interactions are perceived as essential for success in the VC industry, both for the selection and treatment of investments. The arrival of the Covid-19 pandemic, followed by restrictions on in-person meetings, put this investment model to the test. By replacing face-to-face interactions with online meetings, the pandemic not only challenged VCs' post-investment activities requiring on-site presence but also changed the quality of soft information that VCs can collect about early-stage companies and the cost of information collection. This setting provides a unique opportunity to test the validity of the VC investment model: how does a change in soft information collection from in-person to online impact the behavior of these active financial intermediaries that highly rely on face-to-face communications? In this paper, we empirically address this question.

We first establish that VCs broke their proximity culture and broadened their geographical horizons. We show that the distance between a VC firm and its portfolio company increases by 19-35% after Covid. This increase in distance is in part explained by a lower likelihood of VCs to invest in their own state. We also find evidence consistent with VCs making careful steps when the collection of extensive soft information or on-site visits are limited. The distance to investment increases more for smaller deals than for large ones, and the distance increases less for startups from capital- and knowledge-intensive industries that might require more substantial information to make the investment decision. These results suggest that online communications could not perfectly substitute for in-person ones, and couldn't completely level the playing field for distant and proximate investments.

This distance growth also reflects some redistribution of VC investments across geographies, with a relative increase in investments outside large entrepreneurial hubs (i.e., San Francisco, San Jose, Oakland, Boston, Cambridge, and New York) and California. Our results suggest that the redistribution of deals towards areas outside entrepreneurial hubs is driven by in-hub VCs that shift their focus to potentially less crowded markets. We also observe an increase in companies' pre-money valuations compared to the pre-Covid period in geographies outside California, consistent with relatively more deals happening there in the post-Covid period. At the same time, we observe that VCs might increase a control grasp on startups located in California, since the average acquired equity share increases slightly. Overall, these results might indicate a change in the competition for deals across geographies.

We then investigate changes in investment characteristics in the post-Covid period. We find that VCs invest in more familiar firms (those in their focus industry and more similar to past VC investments), but these firms are not more likely to be substantially older or to have pre-VC financing. Thus, VCs seem to balance the lack of soft information with their own expertise and they choose businesses that might have a more clear track record by the time of the investment. The syndication process also appears affected by the Covid-induced interruption of in-person communication. Post-Covid, VC syndicates are slightly smaller, but the average distance between syndicate members increases, as does the probability of a VC investing with old syndicate partners. Besides, a syndicate is more likely to have at least one VC specialized in the company's industry. These results are in line with the expected VC behavior, given the need to obtain information about more geographically distant companies and the overall change in the available soft information about private companies. But they also indicate that maintaining a pre-Covid syndicates size might be more difficult in the online world.

Finally, we provide early insights into the performance of VC investments. We show preliminary findings on the probability of having a second round within 12 and 18 months, and also take a look at the probability of companies going public or being acquired within 18 months since their first VC investment. Early findings suggest that companies financed after Covid-19 do not perform worse in terms of the probability to receive the second round and early exits. Thus, if these remote investments are not of poorer quality, this would imply that the old VC investment model requiring in-person interactions between investors and startup teams might be becoming less relevant in the age of Zoom. We might also think that VCs overestimated the importance of in-person interactions, at least for some deals. Nevertheless, due to the short observation period available, these results should be interpreted with caution.

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. VCs reach to wider geography for their investments, deviating from their traditional approach of investing in companies that they can visit easily. The change in the structure and geography of the VC syndication network can be a potential explanation for this unconventional behavior. In fact, VCs expand the geography of their partners but also seem to risk less by leveraging their network: they collaborate with VCs with whom they have prior experience and include VCs that are experts in the portfolio company's industry in the syndicate. Thus, they seem to try to compensate for the lack of in-person due diligence with other mechanisms available to them. This balancing approach suggests that soft information is still crucial for VCs when in-person interactions are restricted because investors look for alternative ways to acquire it. Roelof Botha, the partner of Sequoia Capital mentioned above, says about raising VC financing online: "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]. With this approach to investing, it is not surprising that VCs try to be

[24]From *McKinsey on startups* podcast. See https://www.mckinsey.com/industries/technology-media-and-

vigilant in the new environment.

These results have important implications for VC investors and the geographical spread of entrepreneurial activity. For VCs, the results observed so far might indicate a change in the competitive dynamics. The geography of potential investments expanded, and higher competition for the best deals might result since any fund can reach any startup more easily. Therefore, VCs will have to understand startup founders even better than they used to, to be able to offer tailored investment conditions to secure the best deals from their competitors. Additionally, VC investors need to reinforce their way of managing post-investment activities without being on-site. Another relevant implication of our results is the increasing importance of deal syndication: in the new environment, VCs expand the geographical reach of their syndication network, but they also rely more on well-known partners and combine more industry expertise within the syndicate. These new networks could be persistent and allow VCs with more similar investment interests to pull together resources to finance more innovative entrepreneurial projects irrespective of the partners' location. Finally, 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.

telecommunications/our-insights/global-vc-view-funding-startups-in-the-next-normal.

## 2.9 Tables and Figures

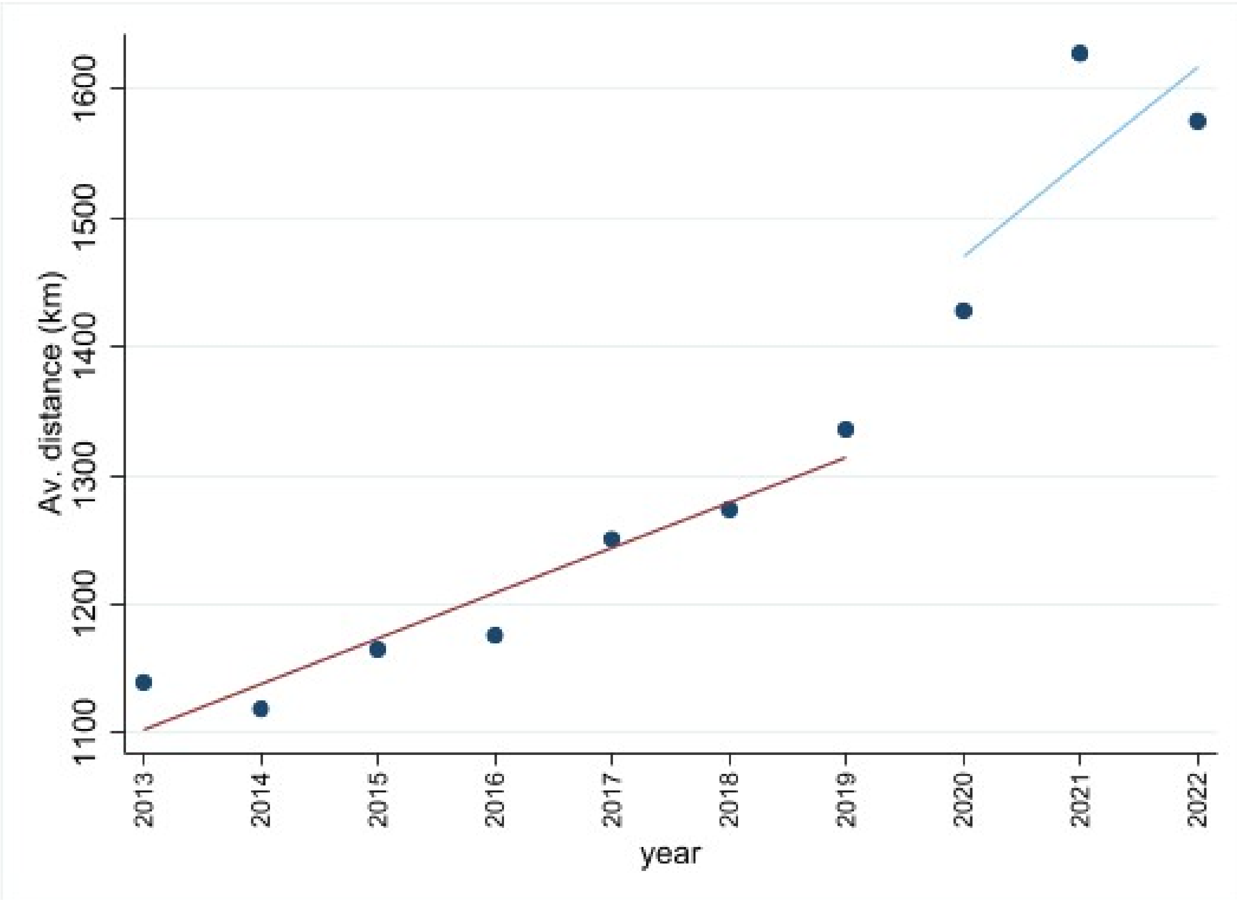


**Figure 2.1. Average distance over time**

plot shows the average distance (in km) between VC firms and their new portfolio companies over years. The sample covers companies that received their first investment round between March 2013 and July 2022 and defined as “seed" and “early stage".

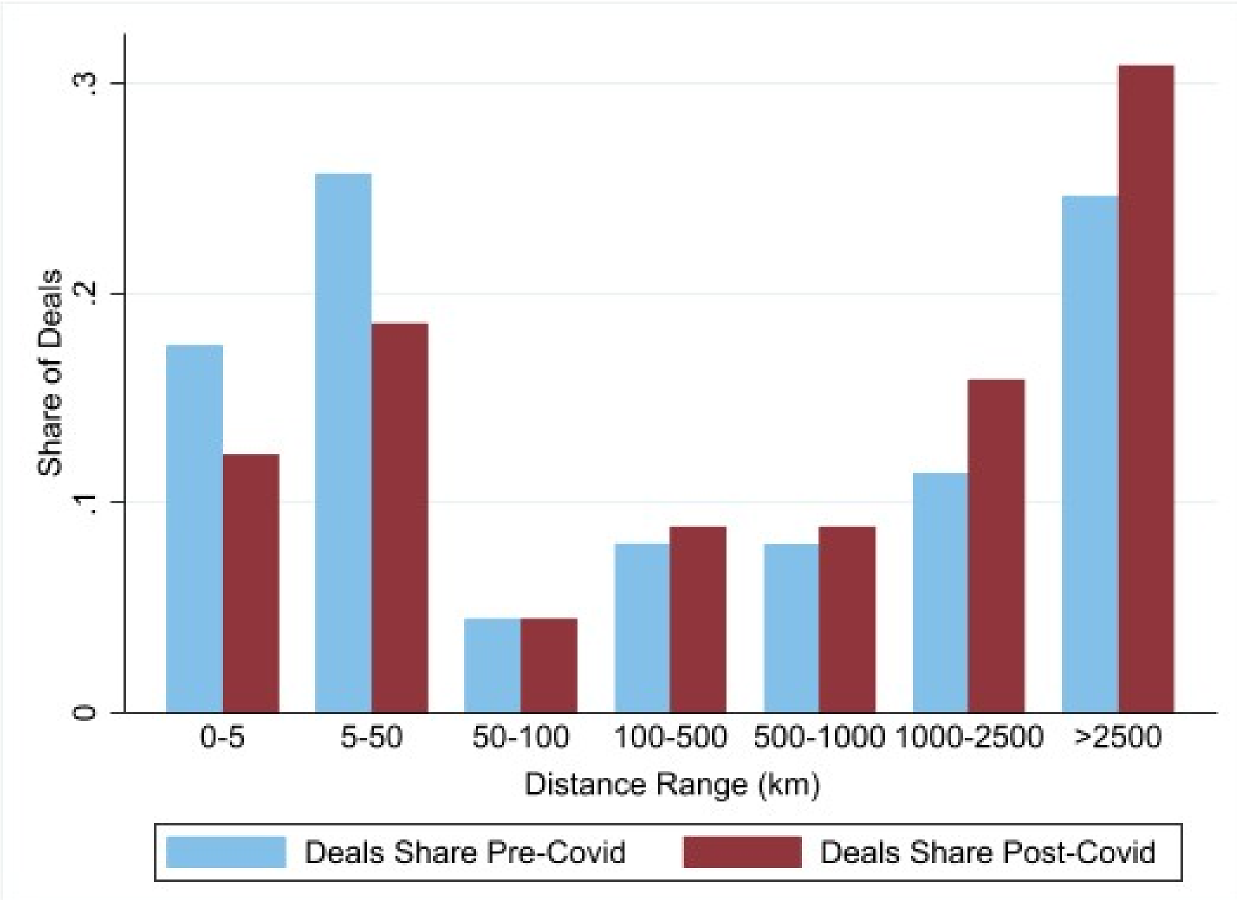


**Figure 2.2. Change in Distribution of Deals by Distance**

The figure reports the shares of deals pre and post-Covid, by different distance ranges (in km). The pre-Covid period is March 2013 - February 2020, and the post-Covid period is March 2020 - July 2022.

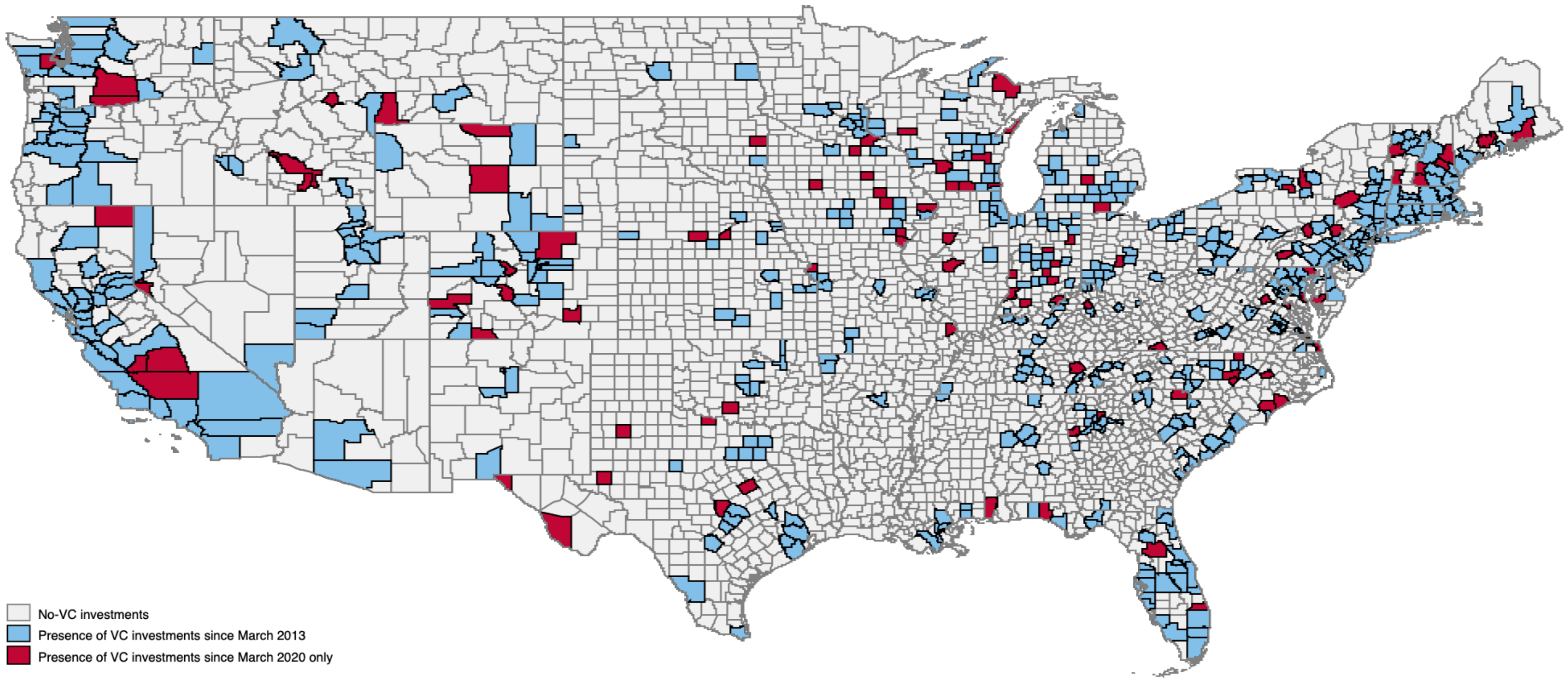


**Figure 2.3. First Investments by VCs post-Covid**

The figure reports a State-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. Panel A reports deal characteristics with the unit of observation at the portfolio company-VC investor pair level. Panel B reports company characteristics at the unique company 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 | Max |
|---|---|---|---|---|---|
| **Panel A: Deal characteristics** | | | | | |
| Distance (km) | 46,652 | 1,318 | 1,635 | 0 | 7,940 |
| Ln(Distance+1) | 46,652 | 5.17 | 2.74 | 0 | 8.98 |
| P(Same State) | 46,652 | 0.51 | 0.50 | 0 | 1.00 |
| Round's N VCs | 46,652 | 3.86 | 2.76 | 1.00 | 28 |
| Round Equity ($ mil) | 46,652 | 7.35 | 26.45 | 0.00 | 2585.75 |
| Ln(Round Equity) | 46,652 | 1.06 | 1.37 | -6.92 | 7.86 |
| P(Seed Round) | 46,652 | 0.64 | 0.48 | 0 | 1.00 |
| **Panel B: Company characteristics** | | | | | |
| Company Age (years) | 19,524 | 3.13 | 2.42 | 0 | 118 |
| CA Company | 19,805 | 0.38 | 0.49 | 0 | 1.00 |
| HUB Company | 19,805 | 0.32 | 0.47 | 0 | 1.00 |
| Pre-money Valuation (deflated) | 11,600 | 15.91 | 38.29 | 0 | 975 |
| Ln(Pre-money Valuation) | 11,598 | 2.18 | 0.95 | -1.29 | 6.80 |
| P(Pre-VC Financing) | 19,805 | 0.26 | 0.44 | 0 | 1.00 |

**Table 2.2. Post-Covid Distance to Investments**

The table reports the results of an OLS regression where the dependent variable is: in columns (1) to (3), one plus the natural logarithm of distance between the VC investor and the startup that received financing; and in columns (4) and (5), 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. 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. Column (3) additionally includes a dummy variable for whether the company is located in an entrepreneurial hub. 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) |
| Post Covid | 0.303*** | 0.194*** | 0.173*** | -0.065*** | -0.031*** |
| | (0.050) | (0.044) | (0.043) | (0.009) | (0.008) |
| Time trend | 0.096*** | 0.081*** | 0.071*** | -0.017*** | -0.012*** |
| | (0.012) | (0.010) | (0.010) | (0.002) | (0.002) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Industry FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| VC FE | | ✓ | ✓ | | ✓ |
| Observations | 46,316 | 45,121 | 45,121 | 46,316 | 45,121 |
| R-squared | 0.025 | 0.251 | 0.272 | 0.055 | 0.304 |

**Table 2.3. Post-Covid Minimum and Maximum Distance to Investments**

The table reports the results of an OLS regression where the dependent variable is: in columns (1) to (3), the natural logarithm of distance between the startup and its most proximate VC investor; in columns (4) to (6), the natural logarithm of distance between the startup and its most remote VC investor. 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. 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. Columns (3) and (6) additionally include a dummy variable for whether the company is located in an entrepreneurship hub. Standard errors are clustered at the VC investor level.*** p<0.01, ** p<0.05, * p<0.1.

| | Ln(Minimum Distance+1) | | | Ln(Maximum Distance+1) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Post Covid | 0.287*** | 0.253*** | 0.224*** | 0.264*** | 0.228*** | 0.219*** |
| | (0.070) | (0.070) | (0.069) | (0.066) | (0.063) | (0.063) |
| Time trend | 0.087*** | 0.069*** | 0.061*** | 0.065*** | 0.070*** | 0.067*** |
| | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Industry FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| VC FE | | ✓ | ✓ | | ✓ | ✓ |
| Observations | 19,663 | 18,443 | 18,443 | 19,663 | 18,443 | 18,443 |
| R-squared | 0.114 | 0.312 | 0.349 | 0.162 | 0.381 | 0.385 |

**Table 2.4. 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. *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. 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 | 0.006 | | | 0.010** | | |
| | (0.004) | | | (0.005) | | |
| Ln(N Covid Cases) | | 0.102** | | | 0.132*** | |
| | | (0.041) | | | (0.036) | |
| Ln(N Covid Deaths) | | | 0.101*** | | | 0.121*** |
| | | | (0.037) | | | (0.043) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Industry FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year-Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| VC State FE | ✓ | ✓ | ✓ | | | |
| VC FE | | | | ✓ | ✓ | ✓ |
| Observations | 46,315 | 46,315 | 46,315 | 45,121 | 45,121 | 45,121 |
| R-squared | 0.050 | 0.051 | 0.051 | 0.255 | 0.255 | 0.255 |

**Table 2.5. 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". 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 | 0.329*** | 0.322*** | 0.342*** | 0.279*** | 0.294*** | 0.232*** |
| | (0.098) | (0.086) | (0.083) | (0.075) | (0.078) | (0.072) |
| Post Covid x Large Deal (Top 50p) | -0.169* | -0.246*** | | | | |
| | (0.097) | (0.090) | | | | |
| Post Covid x Large Deal (Top 25p) | | | -0.387*** | -0.323*** | | |
| | | | (0.107) | (0.102) | | |
| Post Covid x Large Deal (Top 10p) | | | | | -0.491*** | -0.357** |
| | | | | | (0.154) | (0.148) |
| Time Trend | 0.092*** | 0.075*** | 0.091*** | 0.075*** | 0.091*** | 0.074*** |
| | (0.014) | (0.013) | (0.014) | (0.013) | (0.014) | (0.013) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Deal Type FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Industry FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| VC FE | | ✓ | | ✓ | | ✓ |
| Observations | 19,665 | 18,449 | 19,665 | 18,449 | 19,665 | 18,449 |
| R-squared | 0.020 | 0.304 | 0.021 | 0.305 | 0.020 | 0.304 |

**Table 2.6. Post-Covid Distance to Investments by Industry**

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". 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. Standard errors are clustered at the VC investor level. *** p<0.01, ** p<0.05, * p<0.1.

**Panel A.**

| | Ln(Distance+1) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Software | Finance | B2B | B2C | Pharma & Biotech | Healthcare | Hardware | Energy & Materials |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Post Covid | 0.413*** | 0.513*** | 0.299** | 0.323*** | 0.037 | 0.075 | -0.346 | -0.315 |
| | (0.078) | (0.141) | (0.126) | (0.111) | (0.168) | (0.131) | (0.285) | (0.308) |
| Time Trend | 0.092*** | 0.053* | 0.097*** | 0.064*** | 0.118*** | 0.149*** | 0.128*** | 0.206*** |
| | (0.016) | (0.029) | (0.023) | (0.020) | (0.037) | (0.025) | (0.047) | (0.058) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 17,444 | 4,894 | 5,518 | 7,511 | 3,207 | 5,109 | 1,188 | 803 |
| R-squared | 0.027 | 0.027 | 0.032 | 0.021 | 0.041 | 0.030 | 0.032 | 0.054 |

**Panel B.**

| | Ln(Distance+1) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Software | Finance | B2B | B2C | Pharma & Biotech | Healthcare | Hardware | Energy & Materials |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Post Covid | 0.267*** | 0.312** | 0.136 | 0.167 | 0.095 | 0.058 | -0.670 | -0.626 |
| | (0.074) | (0.152) | (0.138) | (0.122) | (0.146) | (0.142) | (0.467) | (0.390) |
| Time Trend | 0.082*** | 0.057* | 0.108*** | 0.055** | 0.066* | 0.130*** | 0.034 | 0.248*** |
| | (0.015) | (0.033) | (0.028) | (0.022) | (0.034) | (0.029) | (0.067) | (0.094) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| VC FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 16,464 | 4,183 | 4,663 | 6,645 | 2,751 | 4,323 | 702 | 471 |
| R-squared | 0.284 | 0.295 | 0.363 | 0.299 | 0.483 | 0.393 | 0.519 | 0.514 |

**Table 2.7. Post-Covid Startups' Location**

The table reports the results of an OLS regression where the dependent variables are: in columns (1) and (2), a dummy variable for whether the company is located in the state of California; and in columns (3) and (4), a dummy variable for whether the company is located in one of the entrepreneurial hubs (i.e., San-Francisco, San Jose, Oakland, Cambridge, Boston, New York). 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 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 Lead VC investor level. *** p<0.01, ** p<0.05, * p<0.1

| | CA Company | | Hub Company | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Post Covid | -0.047*** | -0.026** | -0.020* | -0.023** |
| | (0.011) | (0.011) | (0.011) | (0.011) |
| Time trend | -0.015*** | -0.008*** | -0.012*** | -0.006*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Controls | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ |
| Industry FE | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ |
| VC FE | | ✓ | | ✓ |
| Observations | 19,663 | 18,443 | 19,663 | 18,443 |
| R-squared | 0.143 | 0.364 | 0.083 | 0.285 |

**Table 2.8. Post-Covid Startups' Location by VC Location**

The table reports the results of an OLS regression where the dependent variable is a dummy variable for whether the company is located in one of the entrepreneurial hubs (i.e., San-Francisco, San Jose, Oakland, Cambridge, Boston, New York). 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 investor pair. The sample of investments is split by whether a VC investor is located in an entrepreneurial hub. 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 Lead VC investor level. *** p<0.01, ** p<0.05, * p<0.1

| | Hub Company | | | |
|---|---|---|---|---|
| | VC Located in a Hub | | VC Located outside a Hub | |
| | (1) | (2) | (3) | (4) |
| Post Covid | -0.024** | -0.028** | -0.007 | -0.013 |
| | (0.012) | (0.013) | (0.021) | (0.022) |
| Time trend | -0.007*** | -0.003 | -0.006 | -0.008 |
| | (0.002) | (0.002) | (0.005) | (0.005) |
| Controls | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ |
| Industry FE | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ |
| VC FE | | ✓ | | ✓ |
| Observations | 13,133 | 12,216 | 6,530 | 6,227 |
| R-squared | 0.080 | 0.269 | 0.039 | 0.200 |

**Table 2.9. Post-Covid Distance to Investments - Robustness to State Growth**

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 round". The unit of observation is the portfolio company-VC investor pair. The independent variable *High-Growth State* is a dummy variable equal to one if the company belongs to the state that experienced the above-median change in its growth rate between 2019 and 2020. The state growth rates are calculated as a weighted average of 3-digit NAICS industry growth rates (economy-wide) weighted by the industry's employment shares in the state. *High-Growth State (HBA)* is a dummy variable equal to one if the company belongs to the state that experienced the above-median change in the business applications (HBA) growth rate between 2019 and 2020. 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.

| | Ln(Distance+1) | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Post Covid | 0.303*** | 0.296*** | 0.231*** | 0.294*** | 0.193** |
| | (0.050) | (0.051) | (0.087) | (0.050) | (0.083) |
| High-Growth State | | -0.259* | -0.291* | | |
| | | (0.141) | (0.153) | | |
| Post Covid x High-Growth State | | | 0.103 | | |
| | | | (0.108) | | |
| High-Growth State (HBA) | | | | -0.447*** | -0.499*** |
| | | | | (0.136) | (0.147) |
| Post Covid x High-Growth State (HBA) | | | | | 0.166 |
| | | | | | (0.104) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Industry FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 46,311 | 46,311 | 46,311 | 46,311 | 46,311 |
| R-squared | 0.025 | 0.027 | 0.027 | 0.032 | 0.032 |

**Table 2.10. Probability of Investing in Focus Industry**

The table reports the results of an OLS regression where the dependent variable is: in columns (1) to (4), a dummy variable equal to one if the portfolio company comes from the VC's focus industry, with data at the company-VC investor pair level; in column (5), 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, with data at the company 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. In these regressions, *Ln(Distance+1)* is the natural logarithm of distance between the VC investor and the startup that received financing plus one. 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". 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 in columns (1) to (4) and robust standard errors are presented in column (5). *** p<0.01, ** p<0.05, * p<0.1.

| | P(Startup in VC's Focus Industry) | | | | |
|---|---|---|---|---|---|
| | Each VC-Startup Pair | | | | At Least 1 VC-Startup Pair |
| | (1) | (2) | (3) | (4) | (5) |
| Post Covid | 0.038*** | 0.037*** | 0.034*** | 0.034*** | 0.020** |
| | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) |
| Time Trend | -0.003* | -0.003 | 0.005** | 0.005** | 0.001 |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Ln(Distance +1) | | | | -0.000 | |
| | | | | (0.001) | |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Industry FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| State FE | | ✓ | ✓ | ✓ | ✓ |
| VC FE | | | ✓ | ✓ | |
| Observations | 46,316 | 46,316 | 45,121 | 45,121 | 19,663 |
| R-squared | 0.316 | 0.318 | 0.492 | 0.492 | 0.367 |

**Table 2.11. Startup Similarity to Past Investments**

The table reports the results of an OLS regression where 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 sector during three years before the analyzed deal. The pairwise similarity score is estimated by computing a Jaccard score between two companies' keyword descriptions reported by Pitchbook. In these regressions, *Ln(Distance+1)* is the natural logarithm of distance between the VC investor and the startup that received financing plus one. 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-Lead VC investor pair. Controls include a natural logarithm of the round's equity investment, the number of investors participating in the 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 in a year prior to the first investment's year. 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) |
| Post Covid | 0.119*** | 0.117*** | 0.096*** | 0.097*** |
| | (0.028) | (0.027) | (0.030) | (0.030) |
| Ln(Distance+1) | | | | -0.004 |
| | | | | (0.004) |
| Time Trend | -0.036*** | -0.036*** | -0.031*** | -0.031*** |
| | (0.005) | (0.005) | (0.006) | (0.006) |
| Controls | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ |
| Deal Type FE | ✓ | ✓ | ✓ | ✓ |
| Industry FE | ✓ | ✓ | ✓ | ✓ |
| Company State FE | | ✓ | ✓ | ✓ |
| VC FE | | | ✓ | ✓ |
| Observations | 19,640 | 19,640 | 18,422 | 18,422 |
| R-squared | 0.113 | 0.118 | 0.238 | 0.238 |

**Table 2.12. Company Characteristics: Age and Pre-VC Financing**

The table reports the results of an OLS regression where the dependent variable is: the portfolio company's age (winsorized at 1 and 99 percent) for columns (1) to (3), and a dummy for having a financing round (from accelerators, angels, crowdfunding, etc.) before receiving the first VC financing for columns (4) to (6). Company Age is calculated as the difference between the year of the analyzed investment deal and the year of the company's founding plus one. In all the regressions, *Ln(Distance+1)* is the natural logarithm of distance between the VC investor and the startup that received financing plus one. 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-Lead 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 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 in a year prior to the first investment's year. We also adjust for the seasonality in VC investments by including fixed effects for the month of the first investment. Columns (2)-(3) and (5)-(6) also contain a dummy variable for whether the company is located in an entrepreneurial hub. Columns (4) to (6) includes additional controls such as 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.

| | Portfolio Company's Age | | | 1(Had Pre-VC Financing) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Post Covid | -0.068 | -0.046 | -0.050 | 0.013 | 0.002 | 0.002 |
| | (0.046) | (0.048) | (0.048) | (0.014) | (0.015) | (0.015) |
| Ln(Distance+1) | | | 0.026*** | | | 0.003* |
| | | | (0.006) | | | (0.001) |
| Time Trend | 0.078*** | 0.053*** | 0.051*** | -0.008* | -0.007* | -0.007* |
| | (0.008) | (0.009) | (0.009) | (0.004) | (0.004) | (0.004) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Deal Type FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Industry FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| State FE | | ✓ | ✓ | | ✓ | ✓ |
| VC FE | | ✓ | ✓ | | ✓ | ✓ |
| Observations | 19,388 | 18,186 | 18,186 | 19, 388 | 18, 186 | 18,186 |
| R-squared | 0.048 | 0.243 | 0.244 | 0.105 | 0.260 | 0.260 |

**Table 2.13. Pre-money Valuations and Percent of Equity Acquired**

The table reports the results of an OLS regression where the dependent variable is the natural logarithm of the deal's pre-money valuation (Panel A.) and the percentage of company's equity acquired by investors in the deal (Panel B.). In these regressions, *Ln(Distance+1)* 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 round". The unit of observation is the portfolio company-Lead 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, company age, and the natural logarithm of the total capital raised by VC funds in the VC's state lagged by one year. We also adjust for the seasonality in VC investments by including fixed effects for the month of the first investment. Standard errors are clustered at the VC investor level. *** p<0.01, ** p<0.05, * p<0.1.

**Panel A.**

| | Ln(Pre-Money Valuation) | | | | | |
|---|---|---|---|---|---|---|
| | All | All | All | All | w/o CA | w/o CA |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Post Covid | 0.023 | 0.029 | 0.025 | 0.024 | 0.068** | 0.067** |
| | (0.022) | (0.021) | (0.019) | (0.019) | (0.029) | (0.029) |
| Ln(Distance+1) | | | | 0.004 | | 0.006 |
| | | | | (0.003) | | (0.005) |
| Time Trend | 0.023*** | 0.024*** | 0.019*** | 0.019*** | 0.011* | 0.011* |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.006) | (0.006) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Deal Type FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Industry FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Company State FE | | ✓ | ✓ | ✓ | ✓ | ✓ |
| VC FE | | | ✓ | ✓ | ✓ | ✓ |
| Observations | 11,370 | 11,368 | 10,374 | 10,374 | 5,594 | 5,594 |
| R-squared | 0.618 | 0.624 | 0.712 | 0.712 | 0.706 | 0.706 |

**Panel B.**

| | Percent of Equity Acquired by Investors | | | | | |
|---|---|---|---|---|---|---|
| | All | All | All | All | w/o CA | w/o CA |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Post Covid | 0.612 | 0.502 | 0.730* | 0.744* | 0.168 | 0.183 |
| | (0.384) | (0.382) | (0.410) | (0.410) | (0.568) | (0.568) |
| Ln(Distance+1) | | | | -0.107** | | -0.151 |
| | | | | (0.053) | | (0.096) |
| Time Trend | 0.069 | 0.069 | 0.107 | 0.112 | 0.266** | 0.270** |
| | (0.071) | (0.070) | (0.082) | (0.081) | (0.121) | (0.120) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Deal Type FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Industry FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Company State FE | | ✓ | ✓ | ✓ | ✓ | ✓ |
| VC FE | | | ✓ | ✓ | ✓ | ✓ |
| Observations | 11,215 | 11,213 | 10,224 | 10,224 | 5,494 | 5,494 |
| R-squared | 0.277 | 0.289 | 0.440 | 0.440 | 0.492 | 0.493 |

**Table 2.14. Probability of Deal Syndication and Number of VCs per Round**

The table reports the results of an OLS regression where the dependent variable is a dummy variable equal to one if the deal is syndicated (has more than one VC investor) and zero otherwise in columns (1)-(3), and it is the Ln(Round N. of VCs) in columns (4)-(6). In these regressions, *Ln(Distance+1)* 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 round". The unit of observation is the portfolio company-Lead VC investor pair. Controls include a natural logarithm of the round's equity investment, 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 in a year prior to the first investment's year. We also adjust for the seasonality in VC investments by including fixed effects for the month of the first investment. Standard errors are clustered at the VC investor level. *** p<0.01, ** p<0.05, * p<0.1.

| | P(Syndicated Deal) | | | Ln(Round N. of VCs) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Post Covid | -0.016 | -0.018 | -0.019 | -0.036** | -0.048*** | -0.049*** |
| | (0.012) | (0.013) | (0.012) | (0.016) | (0.016) | (0.016) |
| Ln(Distance+1) | | | 0.003** | | | 0.007*** |
| | | | (0.001) | | | (0.002) |
| Time Trend | -0.002 | 0.015*** | 0.015*** | -0.002 | 0.019*** | 0.018*** |
| | (0.008) | (0.009) | (0.008) | (0.003) | (0.003) | (0.003) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Deal Type FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Industry FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Company State FE | | ✓ | ✓ | | ✓ | ✓ |
| VC FE | | ✓ | ✓ | | ✓ | ✓ |
| Observations | 19,665 | 18,449 | 18,449 | 19,665 | 18,449 | 18,449 |
| R-squared | 0.117 | 0.346 | 0.346 | 0.141 | 0.363 | 0.364 |

**Table 2.15. Distance Among Syndicate Members**

The table reports the results of an OLS regression where the dependent variable is the natural logarithm of one plus average distance among the syndicate members, calculated as one plus the average of distances between all possible pairs of VCs in the syndicate. In these regressions, *Ln(Distance+1)* 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 round". The unit of observation is the portfolio company-VC investor pair. Controls include a natural logarithm of the round's equity investment, the number of investors participating in the round, company age, 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 in a year prior to the first investment's year. We also adjust for the seasonality in VC investments by including fixed effects for the month of the first investment. 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) |
| Post Covid | 0.296*** | 0.281*** | 0.217*** | 0.176*** |
| | (0.037) | (0.036) | (0.038) | (0.036) |
| Ln(Distance+1) | | | | 0.202*** |
| | | | | (0.005) |
| Time Trend | 0.052*** | 0.050*** | 0.036*** | 0.024*** |
| | (0.008) | (0.008) | (0.009) | (0.008) |
| Controls | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ |
| Deal Type FE | ✓ | ✓ | ✓ | ✓ |
| Industry FE | ✓ | ✓ | ✓ | ✓ |
| Company State FE | | ✓ | ✓ | ✓ |
| VC FE | | | ✓ | ✓ |
| Observations | 37,326 | 37,326 | 36,238 | 36,238 |
| R-squared | 0.089 | 0.113 | 0.269 | 0.321 |

**Table 2.16. Average Proportion of Old Syndicate Partners**

vspace0.2cm The table reports the results of an OLS regression where the dependent variable is the proportion of old syndicate partners in the round. Old syndicate partners are those VCs who co-invested together with the focal VC during five years preceding the year of the analyzed investment. The proportion of old syndicate partners in the deal is a sum of all old syndicate partner pairs divided by the total number of VC pairs in this syndicate (based on all possible pairs of VCs participating in the syndicate). In these regressions, *Ln(Distance+1)* 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 round”. The unit of observation is the portfolio company-VC investor pair. Controls include a natural logarithm of the round’s equity investment, the number of investors participating in the round, company age, 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 in a year prior to the first investment’s year. We also adjust for the seasonality in VC investments by including fixed effects for the month of the first investment. 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) |
| Post Covid | 0.040*** | 0.042*** | 0.034*** | 0.036*** |
| | (0.011) | (0.011) | (0.009) | (0.009) |
| Ln(Distance+1) | | | | -0.008*** |
| | | | | (0.001) |
| Time Trend | -0.011*** | -0.011*** | 0.006*** | 0.006*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Controls | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ |
| Deal Type FE | ✓ | ✓ | ✓ | ✓ |
| Industry FE | ✓ | ✓ | ✓ | ✓ |
| Company State FE | | ✓ | ✓ | ✓ |
| VC FE | | | ✓ | ✓ |
| Observations | 37,325 | 37,325 | 36,237 | 36,237 |
| R-squared | 0.013 | 0.024 | 0.311 | 0.314 |

**Table 2.17. Probability to Receive a Second Round of Financing**

The table reports the results of an OLS regression where the dependent variable is a dummy for whether the startup received a second round of financing within 12 months (columns (1) to (3)) and within 18 months (columns (4) to (6)) 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, 2022. The unit of observation is the portfolio company-Lead VC investor pair. Columns (1) to (3) do not include companies that received their first financing from August 2021 onward, and columns (4) to (6) 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). Controls include 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 in a year prior to the first investment's year. We also adjust for the seasonality in VC investments by including fixed effects for the month of the first investment. 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) |
| Post Covid | 0.093*** | 0.092*** | 0.092*** | 0.115*** | 0.109*** | 0.109*** |
| | (0.009) | (0.011) | (0.011) | (0.013) | (0.015) | (0.015) |
| Ln(Distance+1) | | | -0.002 | | | -0.001 |
| | | | (0.001) | | | (0.002) |
| Time Trend | -0.008*** | -0.008*** | -0.008*** | -0.007*** | -0.005** | -0.005** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Deal Type FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Industry FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Company State FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| VC FE | | ✓ | ✓ | | ✓ | ✓ |
| Observations | 17,303 | 16,145 | 16,145 | 15,885 | 14,735 | 14,735 |
| R-squared | 0.023 | 0.135 | 0.135 | 0.038 | 0.166 | 0.166 |

**Table 2.18. Probability to Exit through IPO or M&A**

The table reports the results of an OLS regression where the dependent variable is a dummy for whether the startup went public or was acquired (columns (1) to (3)) within 18 months, and whether it exited via IPO (versus staying private or M&A, columns (4) to (6)), or via M&A (versus staying private, columns (7) to (9)) separately. The regression dataset includes companies that obtained their first VC financing round defined as "seed" or "early round" between March, 2013, and July, 2022. The unit of observation is the portfolio company-Lead VC investor pair. Controls include 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 in a year prior to the first investment's year, 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 (3), and of IPOs and M&A separately in columns (3) to (6) and (7) to (9), respectively. We also adjust for the seasonality in VC investments by including fixed effects for the month of the first investment. Standard errors are clustered at the VC investor level. *** p<0.01, ** p<0.05, * p<0.1.

| | Probability of Exit within 18 Months | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | P(IPO or M&A) | | | P(IPO) | | | P(M&A) | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Post Covid | 0.012** | 0.010* | 0.010* | 0.012* | 0.007 | 0.007 | 0.021*** | 0.021*** | 0.021*** |
| | (0.005) | (0.005) | (0.005) | (0.006) | (0.006) | (0.006) | (0.005) | (0.005) | (0.005) |
| Ln(Distance+1) | | | -0.000 | | | 0.001** | | | -0.001 |
| | | | (0.001) | | | (0.000) | | | (0.001) |
| Time Trend | -0.006*** | -0.007*** | -0.007*** | -0.001** | -0.000 | -0.000 | 0.007*** | 0.007*** | 0.007*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.000) | (0.000) | (0.001) | (0.001) | (0.001) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Deal Type FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Industry FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Company State FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| VC FE | | ✓ | ✓ | | ✓ | ✓ | | ✓ | ✓ |
| Observations | 15,639 | 14,508 | 14,508 | 15,638 | 14,507 | 14,507 | 15,561 | 14,424 | 14,424 |
| R-squared | 0.013 | 0.144 | 0.144 | 0.032 | 0.226 | 0.226 | 0.023 | 0.136 | 0.136 |

# Chapter 3. Regulation A+ Crowdfunding

## 3.1 Introduction

The number of registered initial public offerings (IPOs) by small firms has decreased since 1996 (Gao et al., 2013; Doidge et al., 2013, 2017; Lux and Pead, 2018) and offerings exempt from SEC registration have attracted more attention (Knyazeva, 2016; Ewens and Farre-Mensa, 2020). Regulation A adopted by the SEC under Section 3(b) of the Securities Act in 1936 was an exemption from registration with the SEC that allowed a firm to raise up to $5 million from the general public. However, this regulation was rarely used because firms still had to go state-by-state to get blue sky law approval for their offerings, making Reg A too expensive for raising at most $5 million. As a result, Reg A was amended in the Jumpstart Our Business Startups (JOBS) Act to improve its practicality.

In particular, on June 19, 2015, Title IV (Reg A+) of the JOBS Act went into effect, allowing private small- and medium-sized firms in the U.S. and Canada to raise up to $50 million[1] per year from both accredited and non-accredited investors in the form of debt or equity[2]. My goal in this paper is to investigate whether Reg A+ was a successful amendment or not. In particular, I investigate whether or not firms used this method of financing, what are the characteristics of the firms that used it, what is the effect of raising capital through Reg A+ on the local economy, and whether it substitutes or complements more traditional sources of financing.

Collecting data on Reg A+ filings from 2015 to 2019, I observe that the number of filings[3]

[1]The SEC increased the financing limit to $75 million in 2020.

[2]Reg A+ extends Reg A to two tiers: Tier 1 and Tier 2. Tier 2 offerings are exempt from state registration and qualification requirements, while Tier 1 offerings must comply with the regulations of each state where the securities are going to be offered or sold.

[3]Note that here the number of filings means the number of rounds of Reg A+ financing. In other words,

increased from 67 in 2015 to 246 in 2019, showing an increasing trend in the tendency for raising capital through Reg A+.[4] The data shows that 80% of the filings (636 out of 797) are generated by and 86% of the total financing amount ($2.3 billion out of $2.7 billion) are raised by firms incorporated after 2009 (firms with average age $\approx 2.25$). The average (median) amount raised by all Reg A+ offerings and by firms incorporated after 2009 are $9 million ($3.2 million) and $9.8 million ($4.1 million). These observations show that Reg A+ provides young firms with a viable method of raising capital. Categorizing filings by issuer age and offering status, I show that young firms constitute a larger fraction of issuers that try to use Reg A+, and that they are more likely not to get qualified by the SEC or fail in raising capital through Reg A+. One potential reason for the first observation is that younger firms have limited access to other sources of financing for the amount that can be raised through Reg A+. A potential reason for the second and third observations can be lack of historical information about younger firms to validate that they are promising investments. I observe that on average firms with a higher number of full-time employees are more likely to be deemed qualified by the SEC and have a successful offering. This is consistent with above-mentioned observations because younger firms typically have fewer full-time employees.

I find that real estate investment trusts, financial services, and real estate firms originated 26.7% of all Reg A+ filings, held 40% of successful Reg A+ offerings, and raised 67.4% of the total amount raised through Reg A+ over the sample period. In addition, 54.9% of the Reg A+ filings and 62% of successful Reg A+ offerings were originated by firms located in California, Florida, New York, District of Columbia, and Georgia. However, the top five in terms of the amount of capital raised through Reg A+ are District of Columbia, California, Utah, Florida, and Illinois, raising 65.8% of the total amount.

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the the number of 1-A forms plus the number of 1-A/POS forms filed at least one year after their relevant 1-A form. Each 1-A form filed with the SEC indicates an attempt to raise capital through Reg A+ by an issuer. However, each qualified 1-A form usually allows the issuer to raise capital for one year. To start a new round of financing, the issuer has to file a 1-A/POS form or a new 1-A form. It is worth noting that the number of filings by form type (1-A, 1-A/A,1-A/POS, etc.) in my dataset is exactly the same as that reported by the SEC at https://www.sec.gov/dera/data/dera_edgarfilingcounts.

[4] Reg A+ went into effect on June 19, 2015. As a result, it may be more logical to compare the number of filings (163) in 2016 to that number (246) in 2019, a comparison that shows a 50% increase.

The summary statistics of balance sheet items indicate that firms that successfully raised capital using Reg A+ were in better financial condition than firms that held an unsuccessful offering or were not qualified. More specifically, the average cash holdings, accounts receivables, total assets, total revenue, basic earnings per share, and diluted earnings per share of firms that were successful in raising capital are higher than those of firms that held an unsuccessful offering or were not qualified.[5] In addition, the average (median) total assets for firms with successful Reg A+ offerings, for unqualified firms, and for firms with unsuccessful offerings are \$41.6 million (\$0.5 million), \$5 million (\$0.2 million), \$13.6 million (\$0.08 million). The low level of median total assets decreases the probability that these firms could receive bank loans. In line with this observation, median loan value and median long-term debt are zero for all three groups of firms mentioned above. However, average loan value and average long-term debt for firms with successful Reg A+ offerings are higher than those for the other two groups of firms. This suggests that having debt decreases uncertainty about or is a sign of the quality of a venture.

Next, I examine the effect of raising capital through Reg A+ on the local economy. In order to find this effect, I consider a regression model similar to those in Samila and Sorenson (2011). I observe a small negative [6] and statistically significant correlation between the amount raised through successful Reg A+ offerings in a county and the ensuing unemployment rate in that county.[7] When an issuer files a 1-A form with the SEC, it is not obvious ex ante whether the offering will be approved or how long the approval process might take.[8] As a result, the start and end dates of Reg A+ offerings are not predetermined. However, one might argue that the regression does not show a causal effect of successful Reg A+ offerings on the local economy. On the one hand, it is possible that raising capital using Reg A+ increases economic activity and as a result decreases unemployment. On the other hand, it

[5] The median of accounts receivables, total revenue, basic earnings per share, and diluted earnings per share are zero for all three groups of firms mentioned above.

[6] The small correlation can be due to the age and small size of the firms that use this financing method.

[7] Because the county level GDP is only available until 2018, I only run time series regressions for the unemployment rate.

[8] According to the data, it can take between a few days to more than a year for a 1-A filing to get qualified by the SEC.

is also possible that a third factor, such as improved investment opportunities in a county, affects the timing of successful Reg A+ offerings and the local economy concurrently.

I document an increasing trend in firms' demand for raising capital through Reg A after the JOBS Act amendment (Reg A+) in 2015. Thus, I next address the question posed by Knyazeva (2016, p.27): "One of the key questions is where Regulation A+ will emerge on the continuum of capital raising methods available to small issuers." More specifically, I investigate whether this method provides access to financing to issuers that otherwise would not be able to raise capital or this method substitutes other methods of financing.

The main options for entrepreneurs to raise capital are accelerators, angel investors, venture capitals, and banks. Due to the large amount of capital (up to $50 million) that can be raised using Reg A+, it is not possible to compare raising capital from accelerators and angel investors to raising capital using Reg A+. In addition, it does not seem logical to compare access to bank financing with Reg A+ because the level of total assets in firms that use Reg A+ is low. [9] However, the majority type (equity) of securities offered and the amount raised through Reg A+ offerings, and the low level of total assets in firms that use Reg A+ make VC financing the most comparable source of financing to Reg A+. As a result, I investigate the relation between this new method of financing and traditional VC financing.

Specifically, I investigate whether Reg A+ crowdfunding substitutes for venture capital financing or complements it. The answer to this question will provide insight on the role of crowdfunding in alleviating geographical and industrial frictions in the market for early-stage financing, as well as on the equilibrium outcome of interactions between the preferences of entrepreneurs (crowdfundees) and the crowd (crowdfunders). I divide the complementary role of Reg A+ (return-based crowdfunding) to VC financing into two categories: On the one hand, Reg A+ (return-based crowdfunding) can enable firms in locations or industries that usually do not attract VCs to raise capital from the crowd. On the other hand, Reg A+ filings can provide information about investment opportunities and decrease the search costs for professional investors and thus attract VC financing to industries and locations

[9] The median total assets of firms that successfully raised capital through Reg A+ is $0.5 million.

with Reg A+ filings, alleviating the mostly negative effect of the geographical and industrial concentration of VC activities (?) on access to financing. However, raising capital through crowdfunding may compete with VC financing for several reasons. First, entrepreneurs who use crowdfunding retain control of their firms, while this may not be true for those using VC financing. Second, Reg A+ crowdfunding is typically a much faster and less costly path to an IPO than VC financing. However, entrepreneurs deprive themselves of VCs' expertise and strategic management when choosing crowdfunding over VC financing. Evidence on the substitution of VC financing with crowdfunding can provide some information on the preferences of entrepreneurs and about how the crowd perceives raising capital through crowdfunding by firms in location-industry combinations with high VC financing.

Combining hand-collected data on the Reg A+ filings with the data on seed-stage VC investments, [10] I show that VC investments and Reg A+ offerings are concentrated in different industries. The lack of overlap between the main industries that these two methods of financing are concentrated in decreases the possibility that VC financing will be bypassed in favor of Reg A+ crowdfunding. However, there are 47 industries (out of 93 industries with successful Reg A+ offerings) that are common between the two methods of financing. These industries generated 134 successful crowdfunding campaigns (40% of all successful Reg A+ offerings).[11] As a result, it is still possible to observe crowdfunding is employed instead of VC financing in county-industry combinations with active VC investments or to observe the complementary role of the crowdfunding to VC financing in attracting VCs to invest in new locations. However, the first case does not seem to be probable because I observe that there are few VC investments and Reg A+ offerings that belong to the same county-industry combinations. [12]

On the one hand, the results show that Reg A+ provides access to financing in states that could not attract VC financing. On the other hand, results also show that 33.5% of

[10] I consider seed-stage VC investments smaller than or equal to $50 million from the ThomsonOne dataset.

[11] The number of industries common between the two methods of financing reduces to 37 (out of 77) when I consider firms that were incorporated after 2009. The number of successful crowdfunding campaigns generated by these industries is 110 (41% of all successful Reg A+ offerings).

[12] There are, 14 and 37 successful Reg A+ offerings that respectively belong to county-industry and state-industry combinations that are common between the two methods of financing.

successful Reg A+ issuers are located in California and New York, which have attracted 52.9% of VC investments. However, most of successful crowdfunding campaigns in New York and California are concentrated in industries that VCs did not invest in during my sample period. It is important to note that most of the successful Reg A+ offerings (55/74) in California are not in the top three counties in terms of number and amount of VCs' investments. I conclude that although Reg A+ issuers and firms that receive VC financing have geographical location overlap, most of them are active in different industries. My results provide support for one aspect of the complementary role of Reg A+ financing to VC financing which is providing access to financing in locations or industries that have not been able attract VC financing.

Finally, I show that there is a positive and statistically significant correlation between the number of successful Reg A+ offerings in a county and the number of ensuing VC investments in that county. The results are similar to the findings of studies on the relation between reward- or donation-based crowdfunding and VC investments (Sorenson et al., 2016; Yu et al., 2017). The previously mentioned consideration regarding the uncertainty in the start dates of Reg A+ offerings holds in this case too. However, one might still argue that the results do not show a causal relation between the number of successful Reg A+ offerings and the number of ensuing VC investments in a county. On the one hand, it is possible that a successful Reg A+ offering[13] decreases uncertainty and search cost for VCs and incentivizes them to search for investment opportunities in new geographical locations. In other words, cheap information about possible investment opportunities in other locations or industries may alleviate the high geographical and industry concentration (Chen et al., 2010b; Sorenson and Stuart, 2001) in the VC industry. On the other hand, there may be some confounding variables, such as an increase in investment opportunities in a location, that affect both the timing of successful Reg A+ offerings and the number of VC investments in a region.

In summary, Reg A+ seems to be an important and rising source of financing that has attracted mostly (80% of the sample) young firms with an average age of two years at the time

[13]It is possible that VCs invest in a firm with successful Reg A+ offering at a later stage or they may invest in similar firms in that location at any stage of financing.

of filing. This method of financing enables firms to raise capital in locations and industries that have not been able to attract VC financing, alleviating geographical and industrial frictions in the market for early stage financing. It does not seem that crowdfunding is a substitute for other common methods of financing for entrepreneurs. One possibility is that the ventures that are financed by Reg A+ are low quality and issuers try to take advantage of unsophisticated investors. Another possibility is that the crowd perceives using Reg A+ by a firm that can attract financing from other sources as a negative sign and avoids investing in that firm. Finally, it seems that the number of (the amount raised through) successful Reg A+ offerings in a region is positively (negatively) correlated with the number of ensuing VC investments (with the unemployment rate) in that region.

The remainder of the paper is organized as follows. In Section 2, I provide a review of the related literature and explain the contributions of this paper. In Section 3, I introduce Reg A+. In Section 4, I describe the data and explain the data collection process. In Section 5, I discuss the firms that filed for Reg A+ and their offerings.In Section 6, I examine the relation between Reg A+ financing and the local economy. In Section 7, I investigate the relation between Reg A+ and traditional sources of financing. In Section 8, I describe role of successful Reg A+ offerings in attracting ensuing VC investments. I conclude in Section 9.

### 3.2 Related Literature

This paper is related to a strand of literature concentrated on the outcomes of the JOBS Act. (Dambra et al., 2015) show that passage of Title I of the JOBS Act (also known as the "IPO on-ramp") in 2012 had a positive effect on the number of IPOs by emerging growth companies (EGCs). (Lewis and White, 2020) investigate the effect of Title I of the JOBS Act on biotech startups and show that the passage of Title I of the JOBS Act led to a 200% increase in biotech IPOs, 30% increase in IPO proceeds, and higher growth in employment. In addition, because compliance costs decrease, biotech startups go public earlier. Two other papers that investigate the effect of Title I of the JOBS Act on the IPO market are

(Barth et al., 2017) and (Chaplinsky et al., 2017). In addition, (Gupta and Israelsen, 2014) argue that lower disclosure requirements in the JOBS Act increases the issuer's cost due to information asymmetry. More specifically, they show that IPO underpricing and post-IPO illiquidity increase.

While several papers examine the effect of Title I of the JOBS Act, only (Knyazeva, 2016) provides a description of data on Reg A+ (Title IV of the JOBS Act) filings from June 2015 to October 2016. However, due to the low activity of issuers in the early part of sample, some questions remain unanswered. In this paper, I provide a comprehensive summary of the data on Reg A+ fillings from 2015 to 2019, showing that this amendment had a positive effect on the usage of Reg A by small- and medium-sized firms. In addition, I answer some outstanding questions in the literature regarding this method of financing, its effect on the local economy, and its relation with more traditional sources of financing.

My paper also contributes to the literature on the interplay between crowdfunding and traditional sources of financing. (Butler et al., 2017) show that crowdfundees (entrepreneurs) request better terms on lending-based platforms when bank financing is more accessible. (Drover et al., 2017) and (Signori and Vismara, 2018) provide evidence that the probability of follow-on financing (including VC financing) decreases with the number of a start-up's crowdfunders on an equity-based platform. Investigating the interplay between reward-based crowdfunding and angel investors' activities,(Yu et al., 2017) show that Kickstarter projects in a region lead to increased angel investors' activities. (Roma et al., 2017) show that the probability of attracting professional investors is positively correlated with the amount of capital raised through reward-based crowdfunding. But (Thies et al., 2019) show that there is an inverted U-shaped relation between the funding-ratio in a successful crowdfunding campaign on Kickstarter and the probability of receiving follow-on VC financing.

In addition, (Sorenson et al., 2016) show that reward-based crowdfunding campaigns attract VCs to invest in counties they previously ignored, in a role that complements VCs. In contrast to the aforementioned papers that investigate whether reward-based crowdfunding is a substitute or complement of traditional sources of financing, in this study I investigate the relation between return-based (debt and equity) crowdfunding and VC financing. I am the first to test this hypothesis using US return-based crowdfunding data.

This paper is also related to the literature examining different channels through which entrepreneurs can decrease high uncertainty regarding their venture and attract external funding. Some studies concentrate on the effects of entrepreneurs' or crowdfundees' choices on the probability of a successful VC financing round or crowdfunding campaign. Among the studied channels in the crowdfunding literature are the level of equity retention in equity crowdfunding campaigns (Vismara, 2016), soft information, high valuation of the start-up, and entrepreneur's prior success (Estrin et al., 2016), positive signs related to human capital and the presence of patents (Ahlers et al., 2015), entrepreneurs' narratives on lending platforms (Herzenstein et al., 2011), visual appearance (Duarte et al., 2012), and social capital (Lin et al., 2013; Polzin et al., 2018). In the VC literature, several papers show that entrepreneurs use different ways to demonstrate the quality of their ventures or their abilities. For example, (Hsu, 2007) finds that prior founding experience, team members with doctoral degrees, and founder's ability to recruit executives using his own network increase the probability of receiving VC financing.

However, given the geographical and industrial concentration of VC activities (Sorenson and Stuart, 2001; Chen et al., 2010b), a successful crowdfunding campaign or a crowdfunding filing may be a channel that decreases the search cost for professional investors, and attracts more professional sources of financing within a specific geographical location. In this paper, I investigate this possibility by studying the effect of successful crowdfunding campaigns on the ensuing VC activities in the same geographical locations. If these two sources of financing play a complementary role, then crowdfunding may help alleviate the failure of VCs in financing early-stage start-ups due to geographical or industry distance and have a positive effect on the aggregate quantity of successful start-ups.

### 3.3 Regulation A+

Under Title IV of the JOBS Act (Reg A+) that went into effect on June 19, 2015, two types of offerings (mini-IPO) are possible: 1) Tier 1 offering that has a $20 million offering limit (up to $6 million secondary sales) in any 12-month period. 2) Tier 2 offering that has a $50 million[14] offering limit (up to $15 million secondary sales)[15] in any 12-month period.

In Reg A+, Tier 2 offerings are exempted from getting state-by-state blue sky law approvals. Even in Tier 1 offerings, firms can use the North American Securities Administrators Association's (NASAA's) coordinated review program for Reg A+, which enables Tier 1 issuers to get compliance with blue sky laws in all the states they want to offer and sell securities at once. As a result, it seems that Reg A+ offerings should be less time-consuming and costly than Reg A offerings.

Firms can apply to offer securities under Reg A+ by filing an offering statement called a 1-A form with the SEC. After the SEC reviews the offering statement, it will issue a notice of qualification on EDGAR if the offering statement is qualified. A firm can start to sell securities after its offering statement is qualified. Reg A+ provides firms with an option called "testing the waters," which allows firms to solicit potential investors before pursuing a Reg A+ offering. In other words, firms can use a testing the waters campaign to observe how much potential investors are willing to invest in the firm. On some crowdfunding platforms such as SeedInvest, testing the waters is completely free.

Table 3.1[16] shows the key differences between Tier 1 and Tier 2 offerings. It suggests that a Tier 1 offering has the minimum requirement for ongoing reporting. More specifically, a firm that finishes a Tier 1 offering is required to file only an exit report, known as a Form 1-Z, not later than 30 calendar days after termination or completion of an offering. However, firms that choose a Tier 2 offering must file annual reports using Form 1-K, semi-annual reports using Form 1-SA, and current reports using Form 1-U; however, filing a Form 1-Z is not mandatory for a Tier 2 issuer as long as that information is reported in other forms such

[14] In 2020, the SEC increased the financing limit of Tier 2 offerings to $75 million.
[15] From 2020, issuers can sell upto $22.5 million on behalf of selling security holders in a Tier 2 offering.
[16] https://www.seedinvest.com/blog/jobs-act/raising-capital-reg-a-mini-ipo.

as a Form 1-K. Although a Tier 2 offering has more burdensome reporting requirements, a firm that completes a Tier 2 offering successfully can list its security, after filing a short registration statement known as Form 8-A, on a national securities exchange, such as the NASDAQ or NYSE, or can list its security on other markets, such as the OTCQB or OTCQX to increase the liquidity of the offered security. Listing a Reg A+ offering security on a national exchange is less time consuming and costly because the issuer does not need to file a Form 10 or Form 1-S. I observe that most of the firms use Reg A+ only to raise capital and they do not get listed on a national exchange afterwards. In addition, the CEOs of firms that use Reg A+ and industry professionals compare this method of financing to VC financing rather than to an IPO.[17]

**[See Table 3.1]**

### 3.4 Data Sources

I assembled three data sets: Reg A+ offerings data set, venture capital investments data set, and patent grants data set. In order to create the first data set, I combined data from SEC Reg A data sets [18] with data from SEC filing data sorted by form type.[19] The SEC Reg A data sets, which have been published quarterly since June 2015, provide data from Forms 1-A, 1-K, and 1-Z and their amendments. Each filing has a unique "ACCESSION NUMBER" and all the available data relevant to that filing can be found using that number. I used the SEC Reg A data sets mainly to get data on each issuer (issuer's name, address, 4-digit SIC code, and year of incorporation), and its security offering [offering amount, security type, offering type (Tier 1 or 2 offering), number of states or territories in which the security was offered, and number of states or territories in which a dealer was used].[20]

[17]Refer to the interview titled "Technology, Artificial Intelligence, and Regulation A+ on Display With Knightscope's Autonomous Security Robots" at https://mapableusa.com/technology-artificial-intelligence-and-regulation-a-on-display-with-knightscopes-autonomous-security-robots/ and Stevens M. Sadler talk on Regulation A+ at the 2016 Crowdfunding Conference and Expo at https://www.youtube.com/watch?v=wYIlUwSo5Jk.

[18]https://www.sec.gov/dera/data/reg-a.

[19]https://www.sec.gov/edgar/searchedgar/accessing-edgar-data.htm.

[20]For comprehensive information on the data provided in the SEC Reg A data, see https://www.sec.gov/files/RegA.pdf

However, the SEC Reg A data sets do not provide data on the minimum offering goal, on the qualification status or qualification date of each filing, on the start, initial closing, and end dates of a qualified offering, and on the amount raised in a successful offering.[21] In order to collect these data points, I had to search the full text provided on EDGAR for each filing. In order to avoid searching firms one by one, I wrote some code that uses the SEC filing data sorted by form type to generate the EDGAR search result URL for each firm. Using these URLs, I hand-collected the previously mentioned data points and completed the Reg A+ offerings data set. Each Form 1-A that gets qualified usually allows the issuer to raise capital for one year,[22] thus if an issuer wants to continue raising capital through Reg A+ beyond the allotted time period, it should file a Form 1-A/POS. I consider each 1-A filing and each 1-A/POS filing that is filed at least one year after qualification of the last Reg A+ filing as a new round of financing; as a result, an issuer can have several rounds of financing. In addition, all the data collected are at the financing round level, not at the issuer level.

Another data point that is not provided in the SEC Reg A data sets is the county in which the issuer is located. However, each issuer's ZIP Code and address is provided. In order to get the county name and the county FIPS code for each issuer, I wrote some code for web scraping that searches the ZIP Code and the state for each issuer on a certain website, [23] saves the county name, and finds the corresponding FIPS code.

To create the VC investments data set, I use the data provided by ThomsonOne. I consider only seed-stage VC investments so that investment amounts are comparable to the possible amount of financing under Reg A+. The ThomsonOne data does not contain SIC codes; however, it contains SIC industry descriptions. In order to match these descriptions with the industry classification used in SEC filings, I use a fuzzy matching method, which matches texts based on Levenshtein distance. The Levenshtein distance is the minimum

[21] Many firms that use Reg A+ do not file a Form 1-Z and only report the amount raised in the 1-K, 1-SA, 1-U, or 253G2 form. The reason is that filing a From 1-Z is mandatory for a Tier 1 offering but not for a Tier 2 issuer as long as that information is reported in Form 1-K. See: https://www.sec.gov/info/smallbus/secg/regulation-a-amendments-secg.shtml.

[22] In some 1-A forms, it is mentioned that the issuer can extend the offering for a certain number of months or that the Form 1-A allows the issuer to raise capital for more than a year.

[23] https://www.uscounties.com/zipcodes/search.pl.

number of character edits to transform one word to the other. The fuzzy matching method returns a score out of 100 for each match. It seems that matches with scores larger than 87 are correct in all cases. However, as the match score goes below 88 in less than 5% of cases, I observe wrong matches in some cases. As a result, for cases with scores lower than 88, I find the best match by searching the relevant industry description online [24] to find the relevant SIC code.

The last data set contains data on patent grants in each year and county. I use the bulk patent data set from USPTO PatentViews.[25] The bulk data set contains patent grants in each year; however, the data on the address of inventors is not complete. In order to find the county for each inventor, I wrote some web scraping code that uses the latitude and longitude of each inventor's location to find the corresponding county through the Census Block API. [26] In Table A.1 in the Appendix, I summarize the resulting patent grant dataset by presenting the number of patent grants in each year, along with patent type and patent origin. This table is close to the data provided by the USPTO,[27] validating the accuracy of the data set.

**[See Table A.1]**

### 3.5 A Detailed Look at Regulation A+

Table 3.2 shows the number of Reg A+ offerings in each year based on offering status, offering type (Tier 1 or 2 offering), and security type. I divide Reg A+ filings into eight groups based on their status: 1) unqualified filings: filings that were not qualified by the SEC; 2) successful filings: filings that were qualified by the SEC and the relevant issuers raised at least equal to the minimum financing goal mentioned in their offering circular;[28] 3)

[24] https://siccode.com/.

[25] https://www.patentsview.org/download/.

[26] https://geo.fcc.gov/api/census/.

[27] This data are comparable to the data reported by the USPTO at the following address: https://www.uspto.gov/web/offices/ac/ido/oeip/taf/us_stat.htm. There are 254 Patent grant observations for which inventors' counties cannot be determined and are dropped.

[28] If the offering does not have a minimum financing goal, then acceptance of any positive amount of capital by issuer from investors is considered as a successful offering.

unsuccessful filings: filings that were qualified by the SEC but the amounts raised through the corresponding offerings were below the minimum financing goal mentioned in the offering circulars; 4) abandoned filings: 1-A filings that do not get qualified by the SEC until nine months after their filing dates and the issuers do not correspond with the SEC to provide more information are declared "abandoned" by the SEC through a "SEC STAFF ACTION" filing; 5) withdrawn before qualification: filings that are withdrawn by issuers even before they are qualified; 6) withdrawn after qualification: filings that are withdrawn by issuers after they are qualified; 7) no reporting after qualification: issuers that do not file any report regarding the offering after it is qualified by the SEC;[29] 8) in progress offerings: qualified offerings in 2019 that were in the process of raising capital at the time of data collection.

**[See Table 3.2]**

The sample covers all the offerings filed from June 2015 to the end of 2019. The number of filings increased from 67 in 2015 (163 in 2016) to 246 in 2019, showing a growing demand for raising capital through Reg A+. From 797 filings in the sample, 69 (8.7%) of the filings were not qualified, 332 (41.7%) led to successful offerings, 62 (7.8%) were unsuccessful, and 29 (3.6%) were withdrawn after the qualification. Sixty-seven percent of all the firms chose a Tier 2 offering over a Tier 1 offering.[30] Eighty-four percent of issuers chose to offer equity, 8% chose debt, and the remaining 8% chose other security types. There were 14 filings by foreign firms, 57% of which are Tier 2 offerings and 85.7% of which offer equity.

I divide the sample into firms incorporated after 2009 and those incorporated before 2010 because the sample of firms incorporated after 2009 is comparable in terms of age to the sample of firms in the ThomsonOne data set that received seed-stage VC financing. The average age of firms that received VC financing is 2.25 years, and the average age of firms incorporated after 2009 that had successful Reg A+ offerings is 1.95 years at the time of

[29] I assume that these firms do not raise capital because according to the regulations they must at least file an update on the offering status when it is completed

[30] Although a Tier 2 offering has more reporting requirements, it allows issuers to raise up to $50 million, provides them with the opportunity to list their securities on a national stock exchange, and exempts issuers from complying with some of the blue sky laws.

filing, and 2.28 years at the start of offering. In section 7, I use these comparable samples to investigate whether or not Reg A+ is replacing VC financing.

Table 3.2 shows that in the sub-sample of firms that were incorporated after 2009, 9.7% (62/636) of all filings were not qualified, 42.1% (268/636) led to successful offerings, 8.5% (54/636) were unsuccessful, and 3.6% (23/636) were withdrawn after qualification. In 75.2% of the filings, a Tier 2 offering is chosen, showing that younger firms are more interested in using a Tier 2 offering than older firms. Younger firms may prefer a Tier 2 offering due to the higher offering limit, the exemption from some blue sky laws, or the chance to get listed on a national exchange. For the issuers, 82.4% offered equity, 8.8% offered debt, and the rest offered other types of securities.

Comparing the sample of firms incorporated after 2009 to the whole sample, I find in Table 3.2 that while both young and old firms use Reg A+, 79.8% of all filings and 80.7% of all successful offerings are originated by firms that were incorporated after 2009. A possible reason for this could be that younger firms have more limited access to other sources of financing comparable to the amount possible through Reg A+.

Table 3.3 provides the issuers' age classified by offering status. The average (median) age [31] of firms that the SEC did not qualify to raise capital through Reg A+, firms that had successful Reg A+ offerings, firms that had unsuccessful offerings, and those that withdrew after qualification are respectively 3.4 (2), 5.4 (2), 3.2 (2), and 4.5 (1) years. In addition, the average age of firms incorporated before 2010 (after 2009) that the SEC did not qualify to raise capital through Reg A+, that had successful Reg A+ offerings, that had unsuccessful offerings, and that withdrew after qualification are respectively 17.9 (1.8), 19.6 (2), 14.4 (1.6), and 15.7 (1.6) years. A trend that seems to hold in the main sample[32] and in the two sub-samples is that younger firms are less likely to be qualified by the SEC and more probable to have an unsuccessful offering. The reason could be the lack of historical information for

[31] This is the age at the time of filing for Reg A+.

[32] When comparing the 42.1% success rate in the sample of young firms to the 41.7% success rate in the whole sample, it seems that younger firms have a minimally higher success rate in raising capital. However, the success rate among qualified firms in the young sample is 83.2% while this rate is 84.3% in the whole sample.

assessing the viability of these ventures.

**[See Table 3.3]**

Tables 3.4 and A.2 provide summary statistics on the Reg A+ offerings. The results show that by the end of 2019, \$2.66 billion was raised through Reg A+ crowdfunding, \$2.29 billion of which was raised by firms incorporated after 2009. The average (median) amount raised by successful offerings is \$9 million (\$3.2 million) in one round of financing. Table 4 shows, the average minimum financing goal for successful campaigns is less than one-third of that for unsuccessful campaigns. Each issuer determines, in its offering statement, the minimum financing goal and the deadline before which that goal should be reached to avoid termination of the offering. In addition to determining the minimum financing goal, issuers choose the states/territories in which they want to issue their securities and decide on whether they want to use broker-dealers in any of those states. While the average number of issue territories is lower for successful campaigns than for unsuccessful campaigns, the average number of territories in which a broker-dealer is used is higher for successful campaigns. By the time of data collection, foreign firms had raised \$40.5 million through Reg A+, showing that foreign firms' use of Reg A+ has been limited. It is likely that some of the firms incorporated before 2010 (11 observations) used Reg A+ to do mergers. Approximately \$145 million has been transferred in these transactions, with an average transaction value of \$16 million. No dealer is used in these transactions and the average number of states/territories (18.89) is lower. The observations mentioned above regarding a minimum financing goal and the number of states/territories chosen in Reg A+ offerings also holds for the sample of firms incorporated after 2009. In addition, younger firms with successful Reg A+ offerings use broker-dealers in a larger number of states or territories (see Tables 4 and A-2).

**[See Table 3.4]**

**[See Table A.2]**

Table 3.5 shows the industries with the highest number of successful offerings and the industries with the highest amount raised through Reg A+.[33] Firms in the real estate investment trusts, financial services, and real estate industries originated 26.7% of all Reg A+ filings, held 40% of successful Reg A+ offerings, and raised 67.4% of the total amount raised through Reg A+ over the sample period. In addition, the most successful industries (real estate investment trusts, financial services, and banks) in raising capital through Reg A+ crowdfunding do not engage much in innovative activities and they are already under some supervision by regulators. The reason for the former could be that entrepreneurs in highly innovative industries, which need highly skilled workers, prefer to use more professional sources of financing to take advantage of their expertise. The reason for the latter observation could be the high possibility of adverse selection and moral hazard among firms that try to use return-based crowdfunding to raise capital.

**[See Table 3.5]**

**[See Table A.3]**

Tables A.4 and 3.6 provide similar information on states with the highest number of Reg A+ filings, with the highest number of successful offerings, and with the highest amount of capital raised using Reg A+. The data show that 54.9% of the Reg A+ filings and 62% of successful Reg A+ offerings were originated by firms located in California, Florida, New York, District of Columbia, and Georgia. However, the top five states/territories in terms of amount of capital raised are District of Columbia, California, Utah, Florida, and Illinois, raising 65.8% of the total amount raised through Reg A+.

**[See Table A.4]**

**[See Table 3.6]**

Table 3.7 provides summary statistics on the reported numbers of full-time and part-time employees by issuers at the time of filing with the SEC. Firms that successfully raised capital

[33]See Table A.3 for the industries with the highest number of Reg A+ filings.

using Reg A+ had 8,478 full-time employees and 4,278 part-time employees.[34] Overall, 3,354 of the full-time employees and 3,688 of part-time employees were hired by firms incorporated after 2009, showing that while older firms employ most of the full-time employees, 86% of part-time employees were hired by young firms. The average (median) number of full-time employees of firms that the SEC did not qualify to raise capital through Reg A+, firms that had successful Reg A+ offerings, firms that had unsuccessful offerings, and those that withdrew after qualification are respectively 8.7(2), 26(1), 10.4(2), and 23.1(2). The corresponding numbers for part-time employees are respectively 1.9(0), 13.1(0), 56(0), and 1.4(0). On average, firms with a higher number of full-time employees are more likely to be qualified by the SEC and have a successful offering.[35] The reason could simply be that firms with more established operations have more employees.

**[See Table 3.7]**

Furthermore, the summary statistics of financial statements items in Table 3.8 show that firms that successfully raised capital using Reg A+ were in better financial condition than firms that held an unsuccessful offering or were not qualified. More specifically, the average cash holdings, accounts receivables, total assets, total revenue, basic earnings per share, and diluted earnings per share of firms that were successful in raising capital are higher than those of firms that held an unsuccessful offering or were not qualified.[36] In addition, the average (median) total assets for firms with successful Reg A+ offerings, for unqualified firms, and for firms with unsuccessful offerings, respectively, are $41.6 million ($0.5 million), $5 million ($0.2 million), and $13.8 million ($0.08 million). The low level of median total assets in the sample decreases the probability that these firms could receive bank loans. The median loan value and median long-term debt are zero for all three groups of firms mentioned above.

[34] The highest number of full-time employees is 2,300 and belongs to a firm incorporated before 2010; however, the highest number of part-time employees in the sample is 2,176 and belongs to a firm incorporated after 2009.

[35] This observation is true in both sub-samples. However, the median numbers of full-time employees and of part-time employees in firms incorporated after 2009 show the reverse.

[36] The median of accounts receivables, of total revenue, of basic earnings per share, and of diluted earnings per share are zero for all three groups of firms mentioned above.

However, the average loan value and the average long-term debt for firms with successful Reg A+ offerings are higher than those for the other two groups of firms. This shows that having debt decreases uncertainty about or is a sign of the quality of a venture. Furthermore, as expected, the average (median) total assets in firms incorporated after 2009 is lower than that in firms incorporated before 2010. For example, the average (median) total assets of firms incorporated after 2009 that had a successful offering is \$14.3 million (\$0.48 million) while the numbers for firms incorporated before 2010 are \$158.3 million (\$1.5 million).

**[See Table 3.8]**

The data collected on the market each issuer's security is registered on before and after raising capital through Reg A+ (Table 3.9) shows that out of 164 filings by firms incorporated before 2010, 57 filings offer securities that were not registered on any market, 93 filings offer securities registered on OTC PINK, 5 filings offer securities registered on OTCBB, 4 filings offer securities registered on OTCQB, 3 filings offer securities registered on OTCQX, 1 filing offers a security registered on the TSX Venture Exchange, and 1 filing offers a security registered on the Canadian Stock Exchange (CSE). As Table 3.9 shows, only 4 issuers register their security on an exchange after using Reg A+. Some of the possible reasons for this observation are that issuers may want to use Reg A+ only to raise capital or that they cannot qualify for being registered on any of the exchanges after raising capital through Reg A+.

**[See Table 3.9]**

Finally, I document some facts regarding Reg A+ (return-based crowdfunding) that seem to differentiate it from reward-based crowdfunding. While (Agrawal et al., 2014) provide evidence that the geographical distribution of reward-based crowdfunding campaigns is similar to that of traditional sources of financing, such as VC financing, I find that 35.4% of the amount raised through Reg A+ crowdfunding is by firms incorporated in Washington, DC, which has not attracted VC investments. Moreover, while (Sorenson et al., 2016) observe that reward-based crowdfunding covers a larger number of counties and industries than VC financing, I find that return-based crowdfunding is even more concentrated than VC financing in terms of geographical or industry distribution.[37]

**[See Table A.5]**

**[See Table A.6]**

### 3.6 Regulation A+ and The Local Economy

In this section, I investigate the effect of raising capital through Reg A+ on the local economy at the county level.[38] In order to find the effect of successful Reg A+ offerings on the local economy, I consider a regression model similar to those in Samila and Sorenson (2011). More specifically, I regress the unemployment rate on the lagged amount of capital raised through Reg A+ ($C_{i,t-1}^{Reg_A+}$), lagged unemployment rate ($R_{i,t}^{Unemployment}$), lagged number of patent grants ($N_{i,t-1}^{Patent}$),[39] and lagged population ($Pop_{i,t-1}$) at the county-year level. I include the number of patent grants in the regression since the creation of new firms and using Reg A+ for raising capital can depend on the level of innovative activity in a region. In addition, I include county and year fixed effects to control for differences between counties that are fixed over time, as well as year-specific factors that can affect the outcome variable. The regression model is:

$$R_{i,t}^{Unemployment} = \beta.C_{i,t-1}^{Reg_A+} + \gamma.N_{i,t-1}^{Patent} + \kappa.R_{i,t-1}^{Unemployment} + \rho.Pop_{i,t-1} + \alpha_t + \pi_i + u_{i,t}. \quad (3.1)$$

Table 3.10 presents the results.[40]The results show that there is a strong positive correlation between lagged unemployment rate (lagged population) and current unemployment

[37]Successful Reg A+ offerings by firms incorporated after 2009 are in 77 industries and 30 states while VCs have invested in firms in 118 industries and 42 states over the sample period.

[38]I conduct the empirical analysis at the county level as counties in the same state have different investment opportunities and I find a large difference between counties in the same state in terms of using Reg A+ to raise capital. See Tables A.5 and A.6

[39]Some patents have more than one inventor. Following Samila and Sorenson (2011), if a patent has n inventors in n different counties, I add $1/n$ to the number of patents in each relevant county.

[40]Standard errors are clustered at the county level.

rate. The coefficient for lagged unemployment rate is 0.6 (t-stat=14.85), while the coefficient for lagged population is 0.34 (t-stat=6.24). The signs of both of these coefficients seem logical. The results also show that there is a small negative (-0.00005)[41] and statistically significant correlation between the amount raised through successful Reg A+ offerings in a county and the ensuing unemployment rate in that county. When an issuer files a Form 1-A with the SEC, it is not obvious ex ante whether the offering will be approved and how long it will take to be approved.[42] As a result, the start and end dates of Reg A+ offerings are not predetermined. However, one might argue that the results do not show that Reg A+ offerings exert a causal effect on the local economy. It is possible that raising capital using Reg A+ increases economic activity and as a result decreases unemployment. Conversely, it is also possible that a third factor such as improved investment opportunities in a county affects the timing of successful Reg A+ offerings and the local economy concurrently.

**[See Table 3.10]**

### 3.7 Regulation A+ vs. Traditional Sources of Financing

I next investigate the relation between financing through Reg A+ and more traditional sources of financing for small firms.[43] More specifically, I investigate whether this method of financing provides access to financing to issuers that otherwise would not be able to raise capital from VCs or this method substitutes VC financing.

Given that I consider the possibility of using Reg A+ financing instead of VC financing, I use the data on seed-stage VC financing from 2015 to 2019 with amounts less than or equal to $50 million so that investment amounts and age of the firms in the Reg A+ sample and seed-stage VC investments are comparable.[44] Table 3.11 provides summary statistics for the sample of all seed-stage VC investments and for the seed-stage VC investments with

[41] The small correlation could be due to the age and small size of the firms that use this method of financing.

[42] It can take between few days to more than a year for a Form 1-A filing to get qualified by the SEC.

[43] As I explained in the introduction, VC financing is the most comparable method of financing to Reg A+.

[44] There are 63 investments in the data set on seed-stage VC investments from 2015 to 2019 with investment amounts above $50 million, the maximum amount of fund-raising possible through a Reg A+ offering.

investment amounts below $50 million. The average and median seed-stage VC investments are comparable to the average and median amounts raised through the Reg A+ offerings. The VCs invested around $8.5 billion in seed-stage start-ups from 2015 to 2019, which is three times the amount of financing through Reg A+.

**[See Table 3.11]**

If Reg A+ crowdfunding is used instead of VC financing, I expect to observe some commonalities between industries or locations that use these methods of financing. Tables 3.5, A.3, and 3.12 show that VC investments and Reg A+ offerings are concentrated in different industries; 51.2% of total number of (or 58.6% of total amount of) VC investments are in biological research and computer software, but Reg A+ offerings are mostly from firms in real estate and financial services (40% of all successful campaigns, 26.7% of all filings, and 67.4% of total amount raised [45]). The lack of overlap between the main industries that these two methods of financing are concentrated in decreases the possibility that Reg A+ crowdfunding replaces VC financing. However, there are 47 industries (out of 93 industries with successful Reg A+ offerings) that are common between the two methods of financing. These industries generated 134 successful crowdfunding campaigns (40% of all successful Reg A+ offerings).[46] As a result, it is still possible that VC financing is used instead of crowdfunding in county-industry combinations with active VC investments or to observe the complementary role of the crowdfunding and VC financing in attracting VCs to invest in new locations.

**[See Table 3.12]**

However, I observe that there are a few VC investments and Reg A+ offerings that belong

[45]The sample consists of all firms that filed for a Reg A+ offering independent of the firms' ages. The sample of firms incorporated after 2009 is more comparable to the sample of firms that received seed-stage VC financing in terms of age. In the sample of firms incorporated after 2009, firms in real estate and financial services originate 48% of all successful campaigns and 32% of all filings.

[46]The number of industries common between the two financing methods reduces to 37 (out of 77) when I consider firms that were incorporated after 2009. The number of successful crowdfunding campaigns generated by these industries is 110 (41% of all successful Reg A+ offerings).

to the same county-industry combinations, [47] indicating that either entrepreneurs still prefer VC financing in county and industry combinations that VCs are interested in or that the crowd perceives using crowdfunding by firms that belong to county-industry combinations with a high level of VC investments as a negative signal. In the former case, the preference of entrepreneurs for VCs may be due to the value added services that they provide, including strategic advice (

Tables 3.6 and A.4 show the states with the highest number of Reg A+ filings and highest number of successful offerings. The top five states/territories based on the number of successful Reg A+ offerings are California (22.3%), District of Columbia (14.5%), New York (10.2%), Florida (7.8%), and Georgia (7.2%). Table 3.13 shows that the states with the highest number of VC financing are California (42.5%), Massachusetts (15.8%), New York (10.4%), Pennsylvania (5%), and Washington (4%). These states respectively attracted 45.6%, 25.8%, 8%, 1%, and 3.9% of the total amount invested by VCs in seed-stage start-ups. The results show that the VC industry does not have a seed-stage investment in DC and that Reg A+ is not used by firms in Massachusetts (MA).

**[See Table 3.13]**

Comparing tables 3.6 and 3.13 shows that Reg A+ provides access to financing in states/territories that have not been able to attract VC financing. For example, District of Columbia, Georgia, and Florida, which are among those with the highest number of successful Reg A+ offerings, attracted only 2% of VC financing, while constituting 29.2% of all successful Reg A+ campaigns and 46.2% of the total amount raised through Reg A+. The tables also show that 32.5% of successful Reg A+ issuers are located in California and New York, which have attracted 52.9% of VC investments. However, most of the successful crowdfunding campaigns (31/34) in New York and (47/74)[48] in California are concentrated

[47]There are 14 and 37 successful Reg A+ offerings that respectively belong to county-industry and state-industry combinations common between the two methods of financing.

[48]In the sample of firms that used Reg A+ and were incorporated after 2009, there are 39 out of 60 successful crowdfunding campaigns in California that are concentrated in industries that VCs did not invest in during the sample period.

in industries that VCs did not invest in during the sample period. Tables A.6 and A.7 show that most of the successful Reg A+ offerings (55/74) in California are not in the top three counties in terms of number and amount of VCs' investments. From these observations one can conclude that although Reg A+ issuers and firms that receive VC financing have geographical location overlap, most of them are active in different industries.

Results suggest that Reg A+ financing complements VC financing. In states that have already attracted VC financing, the Reg A+ gives industries that have not been able to attract VC financing the opportunity to raise capital. It also gives the firms in states that are not VC hubs an additional option for raising capital. The results presented in this section support one aspect of the complementary role of Reg A+ that is providing access to financing in locations or industries that could not raise capital from other sources ex-ante. However, another aspect of this complementary role that needs to be tested is reducing uncertainty in the market for early stage financing and attracting VC financing to new locations. It is possible that information available through Reg A+ about firms in industries common between the two methods of financing attract VCs to new locations.

### 3.8 Regulation A+ and New VC Investments

In this section, I investigate whether Reg A+ filings in a county affect ensuing VC financing in that county. The channel that I have in my mind for this relation is the cheap information provided by Reg A+ filings which may help alleviate the geographical and industrial frictions that prevent start-ups from receiving VC investments. Whether a Reg A+ filing gets qualified or not, or whether it is successful or not provides information about the crowd's belief regarding the financial prospect or even the product of a company.[49] In addition, a successful Reg A+ offering provides investors with some basis for comparing firms.

I concentrate on the effect of successful Reg A+ offerings on the ensuing seed-stage VC financing in a county. To test this relation, I regress the number of VC investments ($N_{i,t}^{VC}$) on the lagged number of successful Reg A+ offerings ($N_{i,t-1}^{RegA+}$), the lagged number

[49] Please refer to the following link to see how a firm raised capital through Reg A+ from its customers: https://www.marketwatch.com/story/crowd-curated-music-site-taps-its-users-for-funding-2016-03-22

of patent grants ($N_{i,t-1}^{PatentGrants}$), and lagged population ($Pop_{i,t-1}$ ) at the county-year level. The number of patent grants are included in the regression because it has been shown that there is a positive correlation between receiving VC financing and having patents (Engel and Keilbach (2007); Mann and Sager (2007); and Cockburn and MacGarvie (2009)). In addition, the creation of new firms and using Reg A+ for raising capital can depend on the level of innovative activities in a region. I also include year and county fixed effects in the regression to control for year-specific factors and county-specific heterogeneity that affect the outcome variable. The time series regression is as follows:

$$N_{i,t}^{VC} = \beta . N_{i,t-1}^{RegA+} + \gamma . N_{i,t-1}^{PatentGrants} + \kappa . Pop_{i,t-1} + \alpha_t + \pi_i + u_{i,t}. \tag{3.2}$$

The results are in table 3.14. In line with the papers mentioned above, I find a positive and significant correlation between the number of patent grants and the ensuing number of VC investments. In addition, I find a (positive correlation) coefficient of 0.39 (t-stat. = 2.26) between the number of successful Reg A+ offerings and the number of ensuing VC investments. This result is similar to the findings of studies on the relation between reward- or donation-based crowdfunding and VC investments (Sorenson et al. (2016); Yu et al. (2017)).

As mentioned in Section 6, when an issuer files a Form 1-A, it is not obvious ex ante whether the offering will be approved and how long it will take to be approved. As a result, some random factors may affect the start and end dates of Reg A+ offerings. However, one might still argue that the results do not show a causal relation between the number of successful Reg A+ offerings and the number of ensuing VC investments in a county. It is possible that a successful Reg A+ offering[50] decreases uncertainty and search cost for VCs and incentivizes them to search for investment opportunities in new geographical locations. In other words, cheap information about possible investment opportunities in other locations or industries may moderate the high geographical and industry concentration (Sorenson and

[50]It is possible that VCs invest in a firm with successful Reg A+ offering at a later stage or they may invest in similar firms in that location at any stage of financing.

Stuart (2001);Chen et al. (2010b)) in the VC industry. There may also be some confounding variables (such as an increase in investment opportunities in a location) that affect both the timing of successful Reg A+ offerings and the number of VC investments in a region.

**[See Table 3.14]**

### 3.9 Conclusion

This paper provides a detailed look at Reg A+ which provides a new method of financing for small- and medium-sized firms in the U.S. and Canada. Using hand-collected data on firms that filed for Reg A+ from June 2015 to the end of 2019, I provide comprehensive information on characteristics, and industrial and geographical distributions of these firms. The results show that young firms constitute a large portion of the issuers that used Reg A+ to raise capital and that they are more likely not to get qualified by the SEC or to have an unsuccessful offering. Eighty percent of the Reg A+ filings are generated by firms incorporated after 2009, while 85% ($2.3 billion out of $2.7 billion) of capital raised through Reg A+ is raised by these firms.[51] In addition, the median total assets of firms that raised capital through Reg A+ is $0.5 million, showing that most of the firms that used Reg A+ are small. Firms that are more likely to get qualified by the SEC and raise capital through Reg A+ have a higher number of full-time employees and are in better condition financially. Finally, the results show that the real estate investment trusts, financial services, and real estate industries raised 67.4% of the total amount raised through Reg A+, while firms located in District of Columbia, California, Utah, Florida, and Illinois raised 65.8% of the total amount.

I test whether the amount raised through Reg A+ offerings in a county affects the local economy. I show that there is a small negative and significant correlation between the the amount raised through Reg A+ and the ensuing unemployment rate at the county-year level. Randomness in the amount of time it takes for a Form 1-A to get qualified by the SEC affects the start and end dates of Reg A+ offerings. However, one might argue that the results do not

[51] The average age of these firms at the start of offering is 2.28.

show successful Reg A+ offerings exert a causal effect on the local economy. It is possible that raising capital using Reg A+ increases economic activity, thereby decreasing unemployment. It is also possible that a third factor, such as improved investment opportunities in a county, affects the timing of successful Reg A+ offerings and the local economy concurrently.

I also investigate the relation between Reg A+ crowdfunding and VC financing. I show that Reg A+ crowdfunding facilitates access to financing in states that are not VC hubs and in industries that cannot attract VC financing even in VC hubs, alleviating geographical and industrial frictions in the market for early stage financing. In addition, the results show that at the county level, there is very little overlap between industries that use VC financing and those that use Reg A+ financing, implying either that entrepreneurs still prefer VC financing in region and industry combinations that VCs are interested in or that investors perceive using Reg A+ by firms in county-industry combinations with active VC financing as a negative signal.

Finally, I investigate whether successful Reg A+ offerings can attract VCs to invest in new locations. I show that there is a positive and statistically significant correlation between the number of successful Reg A+ offerings in a county and the number of ensuing VC investments in it. This observation may suggest that Reg A+ filings decrease uncertainty and search cost for VCs, incentivizing them to invest in new geographical locations.

## 3.10 Tables and Figures

**Table 3.1. Differences Between Tier 1 and Tier 2 Regulation A+ Offerings**

| | Reg A+ Offerings | |
|---|---|---|
| | Tier 1 | Tier 2 |
| Maximum Offering | 20,000,000 | 50,000,000 |
| Investor Type | All, including non-accredited investors | All, including non-accredited investors |
| Individual Investment Limit | None | Unaccredited investors: The greater of 10% of their income or 10% of their net worth; Entities: 10% of revenue or net assets; Accredited investors: Unlimited |
| General Solicitation | Unrestricted | Unrestricted |
| Offering Documents | SEC Review and State Review | SEC Review |
| State Pre-emption | No; Coordinated State Review | Yes |
| Financial Disclosures | Reviewed Financials (certain states might require audits) | Audited Financials |
| Ongoing Disclosures | No Ongoing Public Financial Reporting other than a final report on the status of the offering. | Annual and Semi-Annual Public Reporting including Audits |
| Ability to Terminate Ongoing Reporting Requirements | N/A | Less than 300 holders of Reg A+ stock |
| Transfer Restrictions | None | None |

**Table 3.2. Regulation A+ Offerings**
**Panel A**

| | | All firms | | | | | | Firms Incorporated After 2009 | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Offering Status | Filing Year | Total No. Obs. | Offering Type | | Security Type | | | Total No. Obs. | Offering Type | | Security Type | | |
| | | | Tier 1 | Tier 2 | Equity | Debt | Other | | Tier 1 | Tier 2 | Equity | Debt | Other |
| Successful | 2015 | 23 | 9 | 14 | 14 | 6 | 3 | 19 | 6 | 13 | 10 | 6 | 3 |
| | 2016 | 75 | 25 | 50 | 58 | 2 | 15 | 60 | 16 | 44 | 47 | 2 | 11 |
| | 2017 | 86 | 21 | 65 | 70 | 8 | 8 | 68 | 9 | 59 | 53 | 7 | 8 |
| | 2018 | 85 | 15 | 70 | 70 | 6 | 9 | 68 | 2 | 66 | 54 | 5 | 9 |
| | 2019 | 63 | 7 | 56 | 54 | 5 | 4 | 53 | 3 | 50 | 44 | 5 | 4 |
| Subgroup Total No. Obs. | | 332 | 77 | 255 | 266 | 27 | 39 | 268 | 36 | 232 | 208 | 25 | 35 |
| No. Foreign Firms | | 5 | 0 | 5 | 4 | 0 | 1 | 3 | 0 | 3 | 2 | 0 | 1 |
| Unsuccessful | 2015 | 10 | 4 | 6 | 9 | 0 | 1 | 8 | 3 | 5 | 8 | 0 | 0 |
| | 2016 | 24 | 6 | 18 | 23 | 0 | 1 | 18 | 4 | 14 | 17 | 0 | 1 |
| | 2017 | 16 | 3 | 13 | 15 | 0 | 1 | 16 | 3 | 13 | 15 | 0 | 1 |
| | 2018 | 10 | 0 | 10 | 10 | 0 | 0 | 10 | 0 | 10 | 10 | 0 | 0 |
| | 2019 | 2 | 0 | 2 | 2 | 0 | 0 | 2 | 0 | 2 | 2 | 0 | 0 |
| Subgroup Total No. Obs. | | 62 | 13 | 49 | 59 | 0 | 3 | 54 | 10 | 44 | 52 | 0 | 2 |
| No. Foreign Firms | | 1 | 0 | 1 | 0 | 0 | 1 | | | | | | |
| Abandoned | 2015 | 3 | 3 | 0 | 3 | 0 | 0 | 3 | 3 | 0 | 3 | 0 | 0 |
| | 2016 | 5 | 5 | 0 | 5 | 0 | 0 | 5 | 5 | 0 | 5 | 0 | 0 |
| | 2017 | 5 | 2 | 3 | 5 | 0 | 0 | 5 | 2 | 3 | 5 | 0 | 0 |
| | 2018 | 28 | 13 | 15 | 23 | 2 | 3 | 22 | 7 | 15 | 17 | 2 | 3 |
| | 2019 | 22 | 6 | 16 | 22 | 0 | 0 | 20 | 4 | 16 | 20 | 0 | 0 |
| Subgroup Total No. Obs. | | 63 | 29 | 34 | 58 | 2 | 3 | 55 | 21 | 34 | 50 | 2 | 3 |
| No. Foreign Firms | | 2 | 2 | 0 | 2 | 0 | 0 | | | | | | |
| Not Qualified | 2015 | 10 | 6 | 4 | 5 | 5 | 0 | 9 | 6 | 3 | 4 | 5 | 0 |
| | 2016 | 16 | 14 | 2 | 13 | 3 | 0 | 15 | 13 | 2 | 12 | 3 | 0 |
| | 2017 | 10 | 5 | 5 | 7 | 2 | 1 | 10 | 5 | 5 | 7 | 2 | 1 |
| | 2018 | 8 | 5 | 3 | 7 | 1 | 0 | 7 | 4 | 3 | 6 | 1 | 0 |
| | 2019 | 25 | 10 | 15 | 23 | 2 | 0 | 21 | 8 | 13 | 19 | 2 | 0 |
| Subgroup Total No. Obs. | | 69 | 40 | 29 | 55 | 13 | 1 | 62 | 36 | 26 | 48 | 13 | 1 |
| No. Foreign Firms | | 3 | 3 | 0 | 3 | 0 | 0 | 2 | 2 | 0 | 2 | 0 | 0 |

**Table 3.2. Regulation A+ Offerings**
**Panel B**

| | | All Firms | | | | | | Firms Incorporated After 2009 | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Offering Status | Filing Year | Total No. Obs. | Offering Type | | Security Type | | | Total No. Obs. | Offering Type | | Security Type | | |
| | | | Tier 1 | Tier 2 | Equity | Debt | Other | | Tier 1 | Tier 2 | Equity | Debt | Other |
| Withdrawal before qualification | 2015 | 12 | 6 | 6 | 9 | 3 | 0 | 10 | 5 | 5 | 7 | 3 | 0 |
| | 2016 | 26 | 18 | 8 | 17 | 4 | 5 | 23 | 16 | 7 | 15 | 4 | 4 |
| | 2017 | 9 | 4 | 5 | 9 | 0 | 0 | 6 | 2 | 4 | 6 | 0 | 0 |
| | 2018 | 16 | 7 | 9 | 13 | 1 | 2 | 11 | 2 | 9 | 8 | 1 | 2 |
| | 2019 | 18 | 3 | 15 | 15 | 1 | 2 | 13 | 2 | 11 | 12 | 0 | 1 |
| Subgroup Total No. Obs. | | 81 | 38 | 43 | 63 | 9 | 9 | 63 | 27 | 36 | 48 | 8 | 7 |
| No. Foreign Firms | | 1 | 0 | 1 | 1 | 0 | 0 | | | | | | |
| Withdrawal after qualification | 2015 | 3 | 0 | 3 | 3 | 0 | 0 | 2 | 0 | 2 | 2 | 0 | 0 |
| | 2016 | 7 | 3 | 4 | 6 | 1 | 0 | 7 | 3 | 4 | 6 | 1 | 0 |
| | 2017 | 13 | 0 | 13 | 13 | 0 | 0 | 10 | 0 | 10 | 10 | 0 | 0 |
| | 2018 | 4 | 0 | 4 | 4 | 0 | 0 | 3 | 0 | 3 | 3 | 0 | 0 |
| | 2019 | 2 | 1 | 1 | 2 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 |
| Subgroup Total No. Obs. | | 29 | 4 | 25 | 28 | 1 | 0 | 23 | 3 | 20 | 22 | 1 | 0 |
| No reporting after qualification | 2015 | 6 | 5 | 1 | 5 | 0 | 1 | 5 | 4 | 1 | 4 | 0 | 1 |
| | 2016 | 10 | 9 | 1 | 7 | 3 | 0 | 9 | 8 | 1 | 6 | 3 | 0 |
| | 2017 | 13 | 6 | 7 | 13 | 0 | 0 | 10 | 4 | 6 | 10 | 0 | 0 |
| | 2018 | 18 | 11 | 7 | 17 | 1 | 0 | 9 | 2 | 7 | 9 | 0 | 0 |
| | 2019 | 12 | 6 | 6 | 11 | 0 | 1 | 8 | 2 | 6 | 7 | 0 | 1 |
| Subgroup Total No. Obs. | | 59 | 37 | 22 | 53 | 4 | 2 | 41 | 20 | 21 | 36 | 3 | 2 |
| In progress (qualified) | 2019 | 102 | 25 | 77 | 89 | 7 | 6 | 70 | 5 | 65 | 60 | 4 | 6 |
| In progress (qualified Foreign Firms) | 2019 | 2 | 1 | 1 | 2 | 0 | 0 | | | | | | |
| Total No. Obs. (Panels A & B) | | 797 | 263 | 534 | 671 | 63 | 63 | 636 | 158 | 478 | 524 | 56 | 56 |
| Total No. Obs. (Panels A & B excluding 2019) | | 551 | 205 | 346 | 453 | 48 | 50 | 448 | 134 | 314 | 359 | 45 | 44 |
| Total No. Foreign Firms | | 14 | 6 | 8 | 12 | 0 | 2 | 5 | 2 | 3 | 4 | 0 | 1 |
| Mergers by firms Incorporated before 2010 | | 11 | 9 | 2 | 9 | 0 | 2 | | | | | | |

**Table 3.3. Issuer Age by Offering Status**

| | Average age at the time of filing | Median age at the time of filing | Average age at the start of offering | Median age at the start of offering |
|---|---|---|---|---|
| **All Firms** | | | | |
| Successful | 5.36 | 2 | 5.63 | 3 |
| Unsuccessful | 3.2 | 2 | 3.8 | 2 |
| Not qualified | 3.4 | 2 | | |
| Abandoned | 3.6 | 1 | | |
| **Firms Incorporated after 2009** | | | | |
| Successful | 1.95 | 2 | 2.28 | 2 |
| Unsuccessful | 1.55 | 1 | 1.8 | 1 |
| Not qualified | 1.8 | 1 | | |
| Abandoned | 1.4 | 1 | | |
| **Firms Incorporated before 2010** | | | | |
| Successful | 19.6 | 17.5 | 19.9 | 18 |
| Unsuccessful | 14.4 | 12 | 15 | 12.5 |
| Not qualified | 17.9 | 16 | | |
| Abandoned | 19 | 19.5 | | |

**Table 3.4. Regulation A+ Offerings: Summary Statistics (All Firms)**

| Offering Status | Minimum Financing Goal | | | | Amount Raised | | | | Total Amount Raised | Average Number of Issue Territories | Average Number of Dealer Territories |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Mean** | **Median** | **Min** | **Max** | **Mean** | **Median** | **Min** | **Max** | | | |
| | | | | | **All Firms** | | | | | | |
| Successful | 506,990 | 0 | 0 | 13,600,000 | 8,965,006 | 3,160,526 | 2270 | 50,000,000 | 2,662,606,851 | 43.19 | 52.47 |
| Unsuccessful | 2,025,767 | 0 | 0 | 20,000,000 | 0 | 0 | 0 | 0 | 0 | 47.02 | 49.49 |
| Abandoned | 368,778 | 0 | 0 | 10,000,000 | 0 | 0 | 0 | 0 | 0 | 42.90 | 44.34 |
| Withdrawal Before Qualification | 797,498 | 0 | 0 | 10,000,000 | | | | | 0 | 33.6 | 38.13 |
| Withdrawal After Qualification | 1,744,138 | 0 | 0 | 10,000,000 | 0 | 0 | 0 | 0 | 0 | 46.82 | 45.2 |
| Not Qualified | 950,758 | 0 | 0 | 15,000,000 | 0 | 0 | 0 | 0 | 0 | 34.49 | 36.36 |
| No Reporting After Qualification | 176,120 | 0 | 0 | 6,000,000 | 0 | 0 | 0 | 0 | 0 | 30.57 | 30.68 |
| In progress | 338,354 | 0 | 0 | 5,000,000 | | | | | | 46.90 | 54.19 |
| | | | | | **Mergers** | | | | | | |
| Successful | | | | | 16,129,042 | 14,000,000 | 4,069,527 | 35,124,345 | 145,161,381 | 18.89 | 0 |
| Unsuccessful | | | | | 0 | 0 | 0 | 0 | 0 | 25 | 0 |
| No Reporting After Qualification | | | | | 0 | 0 | 0 | 0 | 0 | 17 | 0 |
| | | | | | **Foreign Firms** | | | | | | |
| Successful | 240,000 | 0 | 0 | 1,200,000 | 8,093,631 | 10,000,000 | 1,156,720 | 15,111,436 | 40,468,156 | 61 | 35.5 |
| Unsuccessful | | | | | 0 | 0 | 0 | 0 | 0 | 52 | 0 |

**Table 3.5. Industries with Highest Number of Successful Regulation A+ Filings**

| SIC Code | Industry Description | No. of Successful Filings | % of Successful Filings | SIC Code | Industry Description | % of Total Amount Raised |
|---|---|---|---|---|---|---|
| 6798 | Real Estate Investment Trusts | 65 | 19.6% | 6798 | Real Estate Investment Trusts | 43.9% |
| 6199 | Finance Services | 41 | 12.3% | 6500 | Real Estate | 12.9% |
| 6500 | Real Estate | 27 | 8.1% | 6199 | Finance Services | 10.6% |
| 3711 | Motor Vehicles & Passenger Car Bodies | 14 | 4.2% | 6021 | National Commercial Banks | 3% |
| 6021 | National Commercial Banks | 9 | 2.7% | 6022 | State Commercial Banks | 2.9% |
| 6022 | State Commercial Banks | 9 | 2.7% | 6162 | Mortgage Bankers & Loan Correspondents | 2.8% |
| 7374 | Computer Processing & Data Preparation | 7 | 2.1% | 3089 | Plastic Products, Nec | 1.9% |
| 7372 | Prepackaged Software | 7 | 2.1% | 7370 | Computer Programming, Data Processing, Etc. | 1.1% |
| 7380 | Miscellaneous Business Services | 6 | 1.8% | 4841 | Cable & Other Pay Television Services | 1% |
| 7389 | Business Services, Nec | 5 | 1.5% | 6510 | Real Estate Operators (No Developers) & Lessors | 1% |
| 7370 | Computer Programming, Data Processing, Etc. | 5 | 1.5% | 3711 | Motor Vehicles& Passenger Car Bodies | 0.9% |
| 2833 | Medicinal Chemicals & Botanical Products | 5 | 1.5% | | | |
| | Total No. Successful Offerings | 332 | | Total Amount Raised | $2.7 billion | 100% |
| | Total No. Successful Industries | 93 | | | | |
| | Total No. Successful Industries (Firms Incorporated After 2009) | 77 | | | | |

**Table 3.6. States/Territories with the Highest Number of Successful Regulation A+ Offerings**

| State | No. of Successful Offerings | % of Successful Offerings | State | Amount Raised | % of Total Amount Raised |
|---|---|---|---|---|---|
| CA | 74 | 22.3% | DC | 943,395,000 | 35.4% |
| DC | 48 | 14.5% | CA | 351,253,000 | 13.2% |
| NY | 34 | 10.2% | UT | 161,198,000 | 6% |
| FL | 26 | 7.8% | FL | 157,574,000 | 5.9% |
| GA | 24 | 7.2% | IL | 140,978,000 | 5.3% |
| VA | 15 | 4.5% | GA | 129,280,000 | 4.9% |
| CO | 11 | 3.3% | MI | 100,000,000 | 3.8% |
| AZ | 9 | 2.7% | TX | 74,802,000 | 2.8% |
| IL | 9 | 2.7% | CT | 69,772,600 | 2.6% |
| TX | 9 | 2.7% | NY | 61,609,000 | 2.3% |
| UT | 8 | 2.4% | MO | 57254000 | 2.2% |
| NJ | 5 | 1.5% | CO | 42200000 | 1.6% |
| PA | 5 | 1.5% | VA | 41703000 | 1.6% |
| A1 (British Columbia, Canada) | 4 | 1.2% | OR | 39824000 | 1.5% |
| LA | 4 | 1.2% | NV | 32,254,000 | 1.2% |
| MD | 4 | 1.2% | AZ | 26,065,000 | 1% |
| NV | 4 | 1.2% | | | |
| OR | 4 | 1.2% | | | |
| Total No. of Successful Offerings | 332 | 100% | Total Amount Raised | $2.7 billion | 100% |
| Total No. of Successful Territories | | 39 | | | |
| Total No. of Successful States | | 37 | | | |
| Total No. of Successful Territories (Firms Incorporated After 2009) | | 32 | | | |
| Total No. of Successful States (Firms Incorporated After 2009) | | 30 | | | |

**Table 3.7. Employment by Offering Status**

| | Full-Time Employment | | | | | Part-Time Employment | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Mean** | **Median** | **Min** | **Max** | **Total** | **Mean** | **Median** | **Min** | **Max** | **Total** |
| **All Firms** | | | | | | | | | | |
| Successful | 25.9 | 1 | 0 | 2300 | 8478 | 13.1 | 0 | 0 | 2176 | 4278 |
| Unsuccessful | 10.4 | 2 | 0 | 126 | 646 | 56.1 | 0 | 0 | 3354 | 3473 |
| Not Qualified | 8.7 | 2 | 0 | 248 | 591 | 1.9 | 0 | 0 | 18 | 127 |
| Abandoned | 6.6 | 2 | 0 | 143 | 407 | 6.8 | 1 | 0 | 216 | 419 |
| Withdrawal Before Qualification | 25.9 | 1 | 0 | 2300 | 8478 | 13.1 | 0 | 0 | 2176 | 4278 |
| Withdrawal After Qualification | 23.1 | 2 | 0 | 336 | 669 | 1.4 | 0 | 0 | 8 | 42 |
| **Firms Incorporated After 2009** | | | | | | | | | | |
| Successful | 12.8 | 0 | 0 | 1422 | 3354 | 14.0 | 0 | 0 | 2176 | 3688 |
| Unsuccessful | 9.1 | 1 | 0 | 70 | 489 | 63.6 | 0 | 0 | 3354 | 3434 |
| Not Qualified | 9.4 | 2 | 0 | 248 | 571 | 1.6 | 0 | 0 | 15 | 95 |
| Abandoned | 6.7 | 2 | 0 | 143 | 362 | 7.5 | 1 | 0 | 216 | 408 |
| Withdrawal Before Qualification | 3.3 | 1 | 0 | 70 | 207 | 1 | 0 | 0 | 5 | 60 |
| Withdrawal After Qualification | 8.4 | 1 | 0 | 115 | 193 | 1.2 | 0 | 0 | 5 | 27 |
| **Firms Incorporated Before 2010** | | | | | | | | | | |
| Successful | 80.1 | 8.5 | 0 | 2300 | 5124 | 9.2 | 1.5 | 0 | 115 | 590 |
| Unsuccessful | 19.6 | 5 | 1 | 126 | 157 | 4.8 | 2.5 | 0 | 27 | 39 |
| Not Qualified | 2.9 | 3 | 0 | 6 | 20 | 4.6 | 4 | 0 | 18 | 32 |
| Abandoned | 5.6 | 1.5 | 1 | 31 | 45 | 1.4 | 0 | 0 | 11 | 11 |
| Withdrawal Before Qualification | 32.9 | 5.5 | 2 | 171 | 593 | 4.9 | 1.5 | 0 | 28 | 88 |
| Withdrawal After Qualification | 79.3 | 17 | 0 | 336 | 476 | 2.5 | 1.5 | 0 | 8 | 15 |

**Table 3.8. Financial Statement Items by Offering Status**

| Offering Status | Incorporated Before 2010 | | | | Incorporated After 2009 | | | | All Firms | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Mean** | **Min** | **Max** | **Median** | **Mean** | **Min** | **Max** | **Median** | **Mean** | **Min** | **Max** | **Median** |
| **Total Assets ($ million)** | | | | | | | | | | | | |
| Successful | 158.3 | 0 | 2427.5 | 1.5 | 14.3 | 0 | 491 | 0.48 | 41.6 | 0 | 2427.4 | 0.52 |
| Unsuccessful | 68.8 | $1.12 \times 10^{-4}$ | 546.5 | 0.3 | 5.0 | 0 | 172.1 | 0.02 | 13.8 | 0 | 546.5 | 0.08 |
| Not Qualified | 2.1 | 0.77 | 5.5 | 1.3 | 5.4 | 0 | 121.2 | 0.12 | 5.08 | 0 | 121.2 | 0.15 |
| **Cash Equivalents ($ million)** | | | | | | | | | | | | |
| Successful | 4.6 | 0 | 44.5 | 0.34 | 2.1 | 0 | 62.8 | 0.06 | 2.6 | 0 | 62.8 | $6.8 \times 10^{-2}$ |
| Unsuccessful | 10.1 | $1.12 \times 10^{-4}$ | 80.2 | 0.04 | 0.33 | 0 | 5.95 | $0.7 \times 10^{-2}$ | 1.67 | 0 | 80.17 | $0.9 \times 10^{-2}$ |
| Not Qualified | 0.26 | $4.17 \times 10^{-4}$ | 0.78 | $7.2 \times 10^{-2}$ | 0.16 | 0 | 1.83 | $0.14 \times 10^{-2}$ | 0.17 | 0 | 1.83 | $0.3 \times 10^{-2}$ |
| **Accounts Receivable ($ million)** | | | | | | | | | | | | |
| Successful | 1.70 | 0 | 75.4 | 0 | 1.4 | 0 | 97.5 | 0 | 1.49 | 0 | 97.5 | 0 |
| Unsuccessful | 0.03 | 0 | 0.12 | 0.02 | 0.48 | 0 | 8.4 | 0 | 0.42 | 0 | 8.4 | 0 |
| Not Qualified | 0.16 | 0 | 0.81 | 0.08 | 0.16 | 0 | 3.3 | 0 | 0.16 | 0 | 3.3 | 0 |
| **Total Revenue ($ million)** | | | | | | | | | | | | |
| Successful | 5.8 | 0 | 98.4 | 0 | 1.9 | 0 | 124.8 | 0 | 2.6 | 0 | 124.8 | 0 |
| Unsuccessful | 0.30 | 0 | 1.4 | $1.5 \times 10^{-2}$ | 1.7 | 0 | 70.7 | 0 | 1.54 | 0 | 70.7 | 0 |
| Not Qualified | 0.16 | 0 | 0.7 | 0.03 | 0.63 | 0 | 27.15 | 0 | 0.58 | 0 | 27.15 | 0 |
| **Basic EPS ($)** | | | | | | | | | | | | |
| Successful | 2.12 | -0.99 | 67.66 | 0 | 35.71 | -2162.83 | 9000 | 0 | 29.34 | -2162.83 | 9000 | 0 |
| Unsuccessful | -0.01 | -0.08 | 0.06 | 0 | -36557.93 | -1353010 | 0.62 | 0 | -31515.46 | -1353010 | 0.62 | 0 |
| Not Qualified | -0.04 | -0.29 | 0 | 0 | 1.84 | -11.22 | 113 | 0 | 1.65 | -11.22 | 113 | 0 |
| **Diluted EPS ($)** | | | | | | | | | | | | |
| Successful | 2.08 | -0.99 | 67.66 | 0 | 1.74 | -2162.83 | 3413.61 | 0 | 1.81 | -2162.83 | 3413.61 | 0 |
| Unsuccessful | -0.014 | -0.08 | 0.06 | 0 | -36557.9 | -1353010 | 0.62 | 0 | -31515.46 | -1353010 | 0.62 | 0 |
| Not Qualified | $-4.4 \times 10^{-2}$ | -0.29 | 0 | 0 | 1.817 | -11.22 | 113 | 0 | 1.63 | -11.22 | 113 | 0 |
| **Loans ($ million)** | | | | | | | | | | | | |
| Successful | 76.93 | 0 | 1429.43 | 0 | 1.84 | 0 | 237.45 | 0 | 16.07 | 0 | 1429.43 | 0 |
| Unsuccessful | 53.20 | 0 | 425.56 | 0 | 0 | 0 | 0 | 0 | 7.34 | 0 | 425.56 | 0 |
| Not Qualified | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **Long-Term Debt ($ million)** | | | | | | | | | | | | |
| Successful | 28.14 | 0 | 361.04 | $25.6 \times 10^{-2}$ | 2.17 | 0 | 172.71 | 0 | 7.1 | 0 | 361.04 | 0 |
| Unsuccessful | 2.8 | 0 | 15.8 | 0.421 | 2.59 | 0 | 117.49 | 0 | 2.62 | 0 | 117.49 | 0 |
| Not Qualified | 3.06 | 0 | 20.72 | $1.5 \times 10^{-2}$ | 1.23 | 0 | 35.56 | 0 | 1.42 | 0 | 35.56 | 0 |

**Table 3.9. Market Listing Before and After Using Regulation A+ (Firms Incorporated Before 2010)**

| Market Before Reg A+ | No. of Firms | Market Listing Change After Reg A+ | No. of Firms |
|---|---|---|---|
| OTC PINK | 93 | None → OTC PINK | 1 |
| None | 57 | None → OTCQX | 1 |
| OTCBB | 5 | None → NASDAQ | 1 |
| OTCQB | 4 | None → NYSE | 1 |
| OTCQX | 3 | | |
| TSX Venture Exchange | 1 | | |
| CSE (Canadian Stock Exchange) | 1 | | |
| Total No. | 164 | | |

**Table 3.10. Regulation A+ and Unemployment Rate.** This table reports the results from the time series regression of the unemployment rate on the lagged amount of capital raised through regulation A+ ($C^{Reg_A+}_{i,t-1}$), lagged unemployment rate ($R^{Unemployment}_{i,t}$), lagged number of patent grants ($N^{Patent}_{i,t-1}$), and lagged population ($Pop_{i,t-1}$) at the county-year level.

| | *Coef.* | *Std. Err.* | *t* | $P > \|t\|$ | *95% Conf. Int.* | |
|---|---|---|---|---|---|---|
| Dependent Variable | $R^{Unemployment}_{i,t}$ | | | | | |
| $C^{Reg_A+}_{i,t-1}$ | -0.00005 | 0.00002 | -2.18 | 0.031 | -0.0001 | $-4.97 * 10^-6$ |
| $N^{PatentGrant}_{i,t}$ | 0.3293 | 5.6497 | 0.06 | 0.954 | -10.8333 | 11.4920 |
| $Pop_{i,t-1}$ | 0.3406 | 0.0546 | 6.24 | 0.000 | 0.2328 | 0.4484 |
| $R^{Unemployment}_{i,t-1}$ | 0.5997 | 0.0404 | 14.85 | 0.000 | 0.5199 | 0.6795 |
| *dummy_ 2017* | 369.20 | 1088.70 | 0.34 | 0.74 | -1781.85 | 2520.26 |
| *dummy_ 2018* | 291.76 | 1378.52 | 0.21 | 0.833 | -2431.92 | 3015.435 |
| *dummy_ 2019* | 3842.75 | 2031.80 | 1.89 | 0.060 | -171.6734 | 7857.174 |
| *constant* | -163238.7 | 72631.34 | -2.25 | 0.026 | -306743.6 | -19733.8 |
| No. Obs | 278 | | | | | |
| R-squared (overall) | 0.9987 | | | | | |
| County FE | Yes | | | | | |
| Cluster | County | | | | | |

**Table 3.11. Summary Statistics of Venture Capital Seed-Stage Investments**

| Year | No. Obs. | Amount Raised | | | | Total Amount Raised |
|---|---|---|---|---|---|---|
| | | Mean | Median | Min | Max | |
| 2015 | 200 | 6,110,990.5 | 2,500,000 | 12,000 | 100,000,000 | 1,222,198,100 |
| 2016 | 216 | 11,292,889.81 | 3,900,000 | 25,000 | 225,222,900 | 2,439,264,200 |
| 2017 | 210 | 16,102,873.81 | 5,000,000 | 13,000 | 914,025,000 | 3,381,603,500 |
| 2018 | 287 | 19,567,951.22 | 4,818,000 | 25,000 | 1,000,000,000 | 5,616,002,000 |
| 2019 | 241 | 17,964,055.19 | 5,000,000 | 10,000 | 570,000,000 | 4,329,337,300 |
| Total No. Obs | 1154 | | | | | |
| **Seed-Stage Investments Below $50 million** | | | | | | |
| | | Mean | Median | Min | Max | |
| 2015 | 199 | 5,639,186.432 | 2,500,000 | 12,000 | 49,725,000 | 1,122,198,100 |
| 2016 | 207 | 7,628,155.556 | 3,250,000 | 25,000 | 48,500,000 | 1,579,028,200 |
| 2017 | 199 | 8,258,866.834 | 4,334,000 | 13,000 | 49,000,000 | 1,643,514,500 |
| 2018 | 263 | 8,796,338.783 | 4,250,000 | 25,000 | 45,000,000 | 2,313,437,100 |
| 2019 | 223 | 8,170,799.552 | 4,143,000 | 10,000 | 49,000,000 | 1,822,088,300 |
| Total No. Obs | 1091 | | | | | |

**Table 3.12. Industries with Highest Number of Seed-stage VC Financing (Investments <= $50 million)**

| SIC Code | Industry Description | No. of VC Investments | % of No. VC Investments | % of Amount of VC Investments |
|---|---|---|---|---|
| 7372 | Prepackaged Software | 283 | 25.9% | 19% |
| 8731 | Commercial Physical & Biological Research | 276 | 25.3% | 39.6% |
| 2834 | Pharmaceutical Preparations | 60 | 5.5% | 8.6% |
| 7200 | Personal Services | 49 | 4.5% | 2.8% |
| 3845 | Electromedical & Electrotherapeutic Apparatus | 42 | 3.8% | 2.8% |
| 7374 | Air Courier Services | 39 | 3.6% | 1.2% |
| 3841 | Surgical & Medical Instruments & Apparatus | 32 | 2.9% | 1.8% |
| 7371 | Computer Programming Services | 19 | 1.7% | 1.1% |
| 7370 | Oil & Gas Field Exploration Services | 18 | 1.6% | 1.2% |
| 7389 | Business Services , Nec | 17 | 1.6% | 0.8% |
| 3690 | Public Warehousing & Storage | 11 | 1% | 1.2% |
| 2836 | Biological Products, (No Diagnostic Substances) | 8 | 0.7% | 1.4% |
| Total Obs. | | 1091 | 100% | |
| Total No. of Industries | | 118 | | |

**Table 3.13. States with Highest Number of Seed-stage VC Financing (Investments <= $50 million)**

| State | No. of VC Investments | % of No. VC Investments | % of Amount of VC Investments |
|---|---|---|---|
| CA | 462 | 42.5% | 45.6% |
| MA | 172 | 15.8% | 25.8% |
| NY | 113 | 10.4% | 8% |
| PA | 54 | 5% | 1% |
| WA | 46 | 4.2% | 3.9% |
| TX | 30 | 2.8% | 1.2% |
| NC | 17 | 1.6% | 1% |
| CT | 16 | 1.5% | 1.5% |
| VA | 15 | 1.4% | 1% |
| MN | 14 | 1.3% | 1.2% |
| OH | 13 | 1.2% | 0.5% |
| IL | 10 | 0.9% | 1% |
| UT | 10 | 0.9% | 0.2% |
| MD | 10 | 0.9% | 1% |
| CO | 9 | 0.8% | 0.5% |
| FL | 9 | 0.7% | 1% |
| Total Obs. | 1088 | 100% | |
| Total No. of States | 42 | | |

**Table 3.14. Regulation A+ and New VC Investments.** This table reports the results from time series regression of the number of VC investments ($N_{i,t}^{VC}$) on the lagged number of successful Reg A+ offerings ($N_{i,t-1}^{RegA+}$), the lagged number of patent grants ($N_{i,t-1}^{PatentGrants}$), and the lagged population ($Pop_{i,t-1}$ ) at the county-year level.

$$N_{i,t}^{VC} = \beta.N_{i,t-1}^{RegA+} + \gamma.N_{i,t-1}^{PatentGrants} + \kappa.Pop_{i,t-1} + \alpha_t + \pi_i + u_{i,t}$$

| | *Coef.* | *Std. Err.* | *t* | $P > \|t\|$ | *95% Conf. Int.* | |
|---|---|---|---|---|---|---|
| Dependent Variable | $N_{i,t}^{VC}$ | | | | | |
| $N_{i,t-1}^{Reg_A+}$ | 0.3903 | 0.1725 | 2.26 | 0.025 | 0.0494 | 0.7311 |
| $N_{i,t-1}^{PatentGrant}$ | 0.0057 | 0.0026 | 2.15 | 0.033 | 0.0005 | 0.0109 |
| $Pop_{i,t-1}$ | $-7.6 * 10^{-6}$ | 0.00002 | -0.66 | 0.509 | -0.00003 | 0.00002 |
| *dummy_2017* | -1.2144 | 0.6249 | -1.94 | 0.054 | -2.4492 | 0.0203 |
| *dummy_2018* | -0.2735 | 0.6289 | -0.43 | 0.664 | -1.5161 | 0.9690 |
| *dummy_2019* | -0.9745 | 0.7532 | -1.29 | 0.198 | -2.46 | 0.51 |
| *constant* | 5.3238 | 13.3824 | 0.40 | 0.691 | -21.12 | 31.7648 |
| No. Obs | 278 | | | | | |
| R-squared (overall) | 0.1279 | | | | | |
| County FE | Yes | | | | | |
| Cluster | County | | | | | |

## Appendix A. Data Appendix to Chapter 2: “From in-person to online: the new shape of the VC industry"

**Table A1. Stringency of Covid-related Restrictions by State - Panel A**

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 |

**TABLE A1. Stringency of Covid-related Restrictions by State - Panel B**

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 | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 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 A2. 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) (Refinitiv) | 0.029*** | | -0.011** | |
| | (0.010) | | (0.005) | |
| Ln(Total Funds Size) (Refinitiv) | | 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 A3. 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)-(3) and (6)-(8), the natural logarithm of one plus the distance between the VC investor and the startup that received financing; and in columns (4)-(5) and (9)-(10), 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)-(5)) or from March 2016 to July 2022 (columns (6)-(10)). 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. Columns (3) and (8) additionally include a dummy variable for whether the company is located in an entrepreneurial hub. 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) | (9) | (10) |
| Time trend | 0.087*** | 0.072*** | 0.063*** | -0.015*** | -0.011*** | 0.104*** | 0.105*** | 0.095*** | -0.017*** | -0.016*** |
| | (0.012) | (0.010) | (0.010) | (0.002) | (0.002) | (0.021) | (0.018) | (0.018) | (0.004) | (0.003) |
| Time post | 0.183*** | 0.185*** | 0.167*** | -0.042*** | -0.037*** | 0.176*** | 0.173*** | 0.153*** | -0.040*** | -0.035*** |
| | (0.039) | (0.037) | (0.036) | (0.007) | (0.006) | (0.042) | (0.039) | (0.039) | (0.008) | (0.007) |
| Post | 0.027 | -0.074 | -0.071 | -0.001 | 0.022* | -0.014 | -0.130* | -0.121* | 0.003 | 0.029** |
| | (0.074) | (0.066) | (0.065) | (0.013) | (0.012) | (0.075) | (0.070) | (0.069) | (0.013) | (0.012) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Industry FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| VC FE | | ✓ | ✓ | | ✓ | | ✓ | ✓ | | ✓ |
| Observations | 46,316 | 45,121 | 45,121 | 46,316 | 45,121 | 34,628 | 33,556 | 33,556 | 34,628 | 33,556 |
| R-squared | 0.026 | 0.251 | 0.273 | 0.056 | 0.305 | 0.023 | 0.259 | 0.284 | 0.056 | 0.309 |

**Table A4. Post-Covid Distance to Investments - Robustness to Nb of Deals**

The table corresponds to table 2.2 restricted to VCs with at least 5 deals before and after Covid. It reports the results of an OLS regression where 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) and (5), 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. 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. Column (3) additionally includes a dummy variable for whether the company is located in an entrepreneurial hub. 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) |
| Post Covid | 0.250*** | 0.176*** | 0.163*** | -0.052*** | -0.031*** |
| | (0.065) | (0.052) | (0.051) | (0.012) | (0.009) |
| Time trend | 0.100*** | 0.093*** | 0.082*** | -0.017*** | -0.013*** |
| | (0.017) | (0.012) | (0.012) | (0.003) | (0.002) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Industry FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| VC FE | | ✓ | ✓ | | ✓ |
| Observations | 27,721 | 27,721 | 27,721 | 27,721 | 27,721 |
| R-squared | 0.024 | 0.202 | 0.228 | 0.058 | 0.265 |

**Table A5. Post-Covid Distance to Investments - Robustness to Excluding Accelerators and CVCs**

The table corresponds to table 2.2 excluding investors defined as “Accelerator/Incubator" or "Corporate Venture Capital (CVC)". It reports the results of an OLS regression where 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) and (5), 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. 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. Column (3) additionally includes a dummy variable for whether the company is located in an entrepreneurial hub. 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) |
| Post Covid | 0.307*** | 0.177*** | 0.157*** | -0.067*** | -0.031*** |
| | (0.053) | (0.047) | (0.046) | (0.010) | (0.008) |
| Time trend | 0.099*** | 0.084*** | 0.074*** | -0.017*** | -0.012*** |
| | (0.012) | (0.010) | (0.010) | (0.002) | (0.002) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Industry FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| VC FE | | ✓ | ✓ | | ✓ |
| Observations | 41,348 | 40,416 | 40,416 | 41,348 | 40,416 |
| R-squared | 0.026 | 0.244 | 0.268 | 0.059 | 0.302 |

**Table A6. Post-Covid Distance to Investments - Lead VC**

The table corresponds to table 2.2 with the unit of observation adjusted to portfolio company - Lead VC investor pair. It reports the results of an OLS regression where 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) and (5), 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". 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. Column (3) additionally includes a dummy variable for whether the company is located in an entrepreneurial hub. Standard errors are clustered at the Lead VC investor level. *** p<0.01, ** p<0.05, * p<0.1.

| | Ln(Distance+1) | | | P(Same State) | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Post Covid | 0.257*** | 0.201*** | 0.182*** | -0.056*** | -0.035*** |
| | (0.076) | (0.070) | (0.069) | (0.014) | (0.012) |
| Time trend | 0.084*** | 0.072*** | 0.067*** | -0.014*** | -0.011*** |
| | (0.015) | (0.014) | (0.014) | (0.003) | (0.002) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Industry FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| VC FE | | ✓ | ✓ | | ✓ |
| Observations | 19,663 | 18,443 | 18,443 | 19,663 | 18,443 |
| R-squared | 0.022 | 0.303 | 0.318 | 0.032 | 0.344 |

**Table A7. Growth of Distant Investments and State Growth**

The table reports the results of an OLS regression where the dependent variable is the change in the VC's share of investments in each US state between 2013-2019 and 2020-2022. The regression dataset is at the VC-State level and includes all possible pairs of VCs and U.S. states. The change in investment shares is estimated using the data on the first investment rounds received by companies between March, 2013, and July, 2022 and defined as "seed" or "early round". The independent variable *Ln(Distance VC-State$_i$+1)* is the natural logarithm of 1) the average distance between the VC's office and its investments (where such investments exist) or 2) the distance between the VC's office and the geographical center of State$_i$ estimated in kilometers plus one (for states where VC did not complete any deals). *High-Growth State* is a dummy variable equal to one if the change in the state's growth rate was above the median state growth. State growth was calculated as a weighted average of 3-digit NAICS industry growth rates (economy-wide) between 2019 and 2020, weighted by the industry's employment shares in the state. *High-Growth State (HBA)* is a dummy variable equal to one if the state's business applications growth rate's change was above the median value. All regressions are weighted by the average number of deals performed by the VC investor in pre- and post-Covid periods. Standard errors are clustered at the VC investor level. *** p<0.01, ** p<0.05, * p<0.1

| | Δ Share of VC's Investments in State$_i$ | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Ln(Distance VC-State$_i$+1) | 0.006*** | 0.006*** | 0.003*** | 0.006*** | 0.004*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| High-Growth State$_i$ | | -0.002*** | -0.076*** | | |
| | | (0.000) | (0.009) | | |
| Ln(Distance VC-State$_i$+1) x High-Growth State$_i$ | | | 0.010*** | | |
| | | | (0.001) | | |
| High-Growth State$_i$ (HBA) | | | | -0.002*** | -0.057*** |
| | | | | (0.000) | (0.009) |
| Ln(Distance VC-State$_i$+1) x High-Growth State$_i$ (HBA) | | | | | 0.007*** |
| | | | | | (0.001) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ |
| VC FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 78,438 | 78,438 | 78,438 | 78,438 | 78,438 |
| R-squared | 0.011 | 0.012 | 0.019 | 0.012 | 0.016 |

**Table A8. Post-Covid Distance to Investments - Split by VC Age**

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 round". The unit of observation is the portfolio company-VC investor pair. The sample is split into three categories with respect to VC Age : Young VC, Medium VC and Old VC. 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.

| | Ln(Distance+1) | | |
|---|---|---|---|
| | Young VC (1) | Med VC (2) | Old VC (3) |
| Post Covid | 0.070 | 0.303*** | 0.210*** |
| | (0.086) | (0.086) | (0.076) |
| Time trend | 0.137*** | 0.074*** | 0.051*** |
| | (0.023) | (0.022) | (0.017) |
| Controls | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ |
| Industry FE | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ |
| VC FE | ✓ | ✓ | ✓ |
| Observations | 15,993 | 13,580 | 13,557 |
| R-squared | 0.287 | 0.250 | 0.258 |

**Table A9. Post-Covid Distance to Investments - Split by VC Location**

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 round". The unit of observation is the portfolio company-VC investor pair. The sample of investments is split by whether a VC investor is located in an entrepreneurship hub (i.e., San-Francisco, San Jose, Oakland, Cambridge, Boston, New York). *Hub Company* is a dummy variable equal to one if the portfolio company is located in an entrepreneurship hub and zero otherwise. 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.

| | Ln(Distance+1) | | | |
|---|---|---|---|---|
| | VC Located in a Hub | | VC Located outside a Hub | |
| | (1) | (2) | (3) | (4) |
| Post Covid | 0.235*** | 0.210*** | 0.347*** | 0.182*** |
| | (0.081) | (0.077) | (0.063) | (0.052) |
| Time trend | 0.101*** | 0.098*** | 0.087*** | 0.068*** |
| | (0.023) | (0.021) | (0.014) | (0.011) |
| Controls | ✓ | ✓ | ✓ | ✓ |
| Round FE | ✓ | ✓ | ✓ | ✓ |
| Industry FE | ✓ | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ | ✓ |
| VC FE | | ✓ | | ✓ |
| Observations | 17,865 | 17,592 | 28,451 | 27,529 |
| R-squared | 0.014 | 0.166 | 0.046 | 0.325 |

**Table A10. Presence of Local Syndicate Partners**

The table reports the results of an OLS regression where the dependent variables are: in columns (1) to (3), a dummy variable for whether there is at least one VC within 50 km distance from the startup (excluding the analyzed VC); in columns (4) to (6), the number of other VCs located in within 50km distance from the startup (excluding the analyzed VC). Thus, the regression tries to answer the question "for a specific VC, what is the likelihood that she will have syndicate partners located in the proximity of the portfolio company?". In these regressions, *Ln(Distance+1)* is the natural logarithm of one plus the distance between the analyzed 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 round". 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.

| | P(Local VC in 50km) | | | N Local VCs in 50km | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Post Covid | -0.072*** | -0.074*** | -0.063*** | -0.126*** | -0.130*** | -0.105*** |
| | (0.015) | (0.018) | (0.018) | (0.032) | (0.038) | (0.037) |
| Ln(Distance+1) | | | -0.042*** | | | -0.097*** |
| | | | (0.002) | | | (0.006) |
| Time trend | -0.018*** | -0.016*** | -0.013*** | -0.050*** | -0.045*** | -0.040*** |
| | (0.003) | (0.003) | (0.003) | (0.006) | (0.007) | (0.007) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Stage FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Industry FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| VC FE | | ✓ | ✓ | | ✓ | ✓ |
| Observations | 10,692 | 9,604 | 9,604 | 10,692 | 9,604 | 9,604 |
| R-squared | 0.095 | 0.255 | 0.292 | 0.382 | 0.481 | 0.510 |

## Appendix B. Data Appendix to Chapter 3: Regulation A+ Crowdfunding

This appendix contains the tables that are not extensively discussed in the paper but support some of the claims in the paper. Table A.1 provides a summary of patent grant data set presenting the number of patent grants in each year, patent type, and patent origin. This table can be used to validate the accuracy of the data resulted from processing bulk patent data set provided by USPTO PatentViews. Table A.2 presents summary statistics on Reg A+ filings generated by firms incorporated after 2009. The results show that young firms raised most of the capital financed through Reg A+ (see also Table 3.4). Table A.3 shows the industries with the highest number of Reg A+ filings and Table A.4 shows the states/territories with the highest number of issuers who filed for Reg A+. Tables A.5 and A.6 respectively show the counties with the highest number of Reg A+ filings and with the highest number of successful offerings. The results in these tables suggest that counties in the same state are very different in terms of how active they are in raising capital through Reg A+. This is the reason for conducting regression analyses at the county level. Finally, Table A.7 shows the counties with the highest number and highest amount of VC investments. The results show that counties in California that used Reg A+ are not among top counties in terms of attracting VC investments (also see Table A.6).

**Table A.1. Number of Patent Grants (U.S. Origin and Foreign Origin)[a]**

| Year | Utility Patent Grants, All Origin | Total Design Patent Grants | Total Plant Patent Grants | Reissue Patent Grants | statutory invention registration | Total Patent Grants, U.S. Origin | Total Patent Grants, All Origin |
|---|---|---|---|---|---|---|---|
| 2015 | 299,382 | 26,000 | 1,074 | 513 | | 163,309 | 326,969 |
| 2016 | 304,126 | 28,886 | 1,235 | 427 | | 168,345 | 334,674 |
| 2017 | 320,003 | 30,879 | 1,311 | 394 | | 177,901 | 352,587 |
| 2018 | 308,853 | 30,513 | 1,208 | 529 | 1 | 169,899 | 341,104 |
| 2019 | 355,923 | 34,813 | 1,275 | 607 | | 195,729 | 392,618 |
| Total No. | | | | | | 875,183 | 1,747,952 |

[a] This data is comparable to the data reported by USPTO at the following address: https://www.uspto.gov/web/offices/ac/ido/oeip/taf/us_stat.htm. 254 Patent grant observations for which inventors' counties cannot be determined are dropped.

## Table A.2. Regulation A+ Offerings: Summary Statistics (Firms Incorporated After 2009)

| Offering Status | Minimum Financing Goal | | | | Amount Raised | | | | Total Amount Raised | Average Number of Issue Territories | Average Number of Dealer Territories |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | Median | Min | Max | Mean | Median | Min | Max | | | |
| **Firms Incorporated After 2009** | | | | | | | | | | | |
| Successful | 541,283 | 0 | 0 | 13,600,000 | 9,825,446 | 4,058,086 | 2270 | 50,000,000 | 2,289,328,979 | 47.68 | 55.38 |
| Unsuccessful | 2,060,139 | 0 | 0 | 20,000,000 | 0 | 0 | 0 | 0 | 0 | 47.94 | 50.41 |
| Abandoned | 422,418 | 0 | 0 | 10,000,000 | 0 | 0 | 0 | 0 | 0 | 46.89 | 45.53 |
| Withdrawal Before Qualification | 977,571 | 0 | 0 | 10,000,000 | | | | | 0 | 34.31 | 36.58 |
| Withdrawal After Qualification | 1,981,739 | 0 | 0 | 10,000,000 | 0 | 0 | 0 | 0 | 0 | 47.83 | 53.1 |
| Not Qualified | 1,051,695 | 0 | 0 | 15,000,000 | 0 | 0 | 0 | 0 | 0 | 35.89 | 35.19 |
| No Reporting After Qualification | 257,040 | 0 | 0 | 6,000,000 | 0 | 0 | 0 | 0 | 0 | 36.1 | 33.6 |
| In progress | 492,030 | 0 | 0 | 5,000,000 | | | | | | 52.11 | 55.97 |
| **Foreign Firms** | | | | | | | | | | | |
| Successful | 0 | 0 | 0 | 0 | 11,770,478 | 10,200,000 | 10,000,000 | 15,111,436 | 35,311,436 | 63.7 | 7 |

**Table A.3. Industries with Highest Number of Regulation A+ Filings (All Firms)**

| SIC Code | Industry Description | No. of Filings | % of Filings |
|---|---|---|---|
| 6798 | Real Estate Investment Trusts | 88 | %11 |
| 6199 | Finance Services | 65 | %8 |
| 6500 | Real Estate | 61 | %7.7 |
| 3711 | Motor Vehicles & Passenger Car Bodies | 21 | %2.6 |
| 7374 | Computer Processing & Data Preparation | 20 | %2.5 |
| 7380 | Miscellaneous Business Services | 19 | %2.4 |
| 7997 | Membership Sports & Recreation Clubs | 18 | %2.3 |
| 7389 | Business Services, Nec | 17 | %2.1 |
| 7370 | Computer Programming, Data Processing, Etc. | 17 | %2 |
| 2834 | Pharmaceutical Preparations | 15 | %1.9 |
| 7372 | Prepackaged Software | 14 | %1.8 |
| 7812 | Motion Picture & Video Tape Production | 14 | %1.8 |
| 6022 | State Commercial Banks | 12 | %1.5 |
| 6799 | Investors, Nec | 12 | %1.5 |
| 7900 | Amusement & Recreation Services | 12 | %1.5 |
| | Total No. Obs. | 797 | |
| | Total No. Industries | 170 | |
| | Total No. Industries (Firms Incorporated After 2009) | 140 | |

**Table A.4. States/Territories with the Highest Number of Regulation A+ Filings**

| State | No. of Filings | % of Filings |
|---|---|---|
| CA | 171 | 21.5% |
| FL | 90 | 11.3% |
| NY | 79 | 9.9% |
| DC | 61 | 7.7% |
| GA | 36 | 4.5% |
| TX | 35 | 4.4% |
| IL | 29 | 3.6% |
| UT | 28 | 3.5% |
| NJ | 27 | 3.4% |
| AZ | 24 | 3% |
| CO | 24 | 3% |
| NV | 22 | 2.8% |
| VA | 19 | 2.4% |
| OR | 16 | 2% |
| PA | 14 | 1.8% |
| WY | 11 | 1.4% |
| MD | 10 | 1.3% |
| NC | 10 | 1.3% |
| OH | 9 | 1.1% |
| Total Obs. | 797 | 100% |
| Total No. of Territories | 51 | |
| Total No. of States | 44 | |
| Total No. of Territories (Firms Incorporated After 2009) | 44 | |
| Total No. of States (Firms Incorporated After 2009) | 40 | |

**Table A.5. Counties with Highest Number of Regulation A+ Filings**

| FIPS code | County Name | State | No. of Filings | % of Filings |
|---|---|---|---|---|
| 6037 | Los Angeles | CA | 73 | 9.3% |
| 11001 | District of Columbia | DC | 61 | 7.8% |
| 36061 | New York | NY | 57 | 7.3% |
| 13121 | Fulton | GA | 31 | 4% |
| 6059 | Orange | CA | 27 | 3.4% |
| 12086 | Dade | FL | 21 | 2.7% |
| 6073 | San Diego | CA | 20 | 2.6% |
| 32003 | Clark | NV | 18 | 2.3% |
| 4013 | Maricopa | AZ | 17 | 2.2% |
| 48201 | Harris | TX | 17 | 2.2% |
| 17031 | Cook | IL | 16 | 2% |
| 12095 | Orange | FL | 14 | 1.8% |
| 49035 | Salt Lake | UT | 13 | 1.7% |
| 49043 | Summit | UT | 12 | 1.5% |
| 12099 | Palm Beach | FL | 11 | 1.4% |
| 6075 | San Francisco | CA | 10 | 1.3% |
| 6085 | Santa Clara | CA | 10 | 1.3% |
| 34003 | Bergen | NJ | 10 | 1.3% |
| 8005 | Arapahoe | CO | 9 | 1.1% |
| 12057 | Hillsborough | FL | 8 | 1% |
| Total Obs. | 783 | 100% | | |
| Total No. of counties | 180 | | | |
| Total No. of counties (Firms Incorporated After 2009) | 137 | | | |

**Table A.6. Counties with Highest Number of Successful Regulation A+ Offerings**

| FIPS code | County Name | State | No. of Successful Offerings | % of Successful Offerings |
|---|---|---|---|---|
| 11001 | District of Columbia | DC | 48 | 14.7% |
| 6037 | Los Angeles | CA | 27 | 8.3% |
| 13121 | Fulton | GA | 23 | 7% |
| 36061 | New York | NY | 23 | 7% |
| 6059 | Orange | CA | 15 | 4.6% |
| 6073 | San Diego | CA | 13 | 4% |
| 12086 | Dade | FL | 9 | 2.8% |
| 49035 | Salt Lake | UT | 7 | 2.1% |
| 51059 | Fairfax | VA | 7 | 2.1% |
| 4013 | Maricopa | AZ | 6 | 1.8% |
| 6075 | San Francisco | CA | 6 | 1.8% |
| 12099 | Palm Beach | FL | 6 | 1.8% |
| 6001 | Alameda | CA | 5 | 1.5% |
| 48201 | Harris | TX | 5 | 1.5% |
| 8005 | Arapahoe | CO | 4 | 1.2% |
| 17097 | Lake | IL | 4 | 1.2% |
| 36025 | Delaware | NY | 4 | 1.2% |
| Total Obs. | 327 | 100% | | |
| Total No. of counties | 98 | | | |
| Total No. of counties (Firms Incorporated After 2009) | 70 | | | |

**Table A.7. Counties with Highest Number of Seed-stage VC Financing (Investments <= $50 million)**

| FIPS Code | County | State | No. of VC Investments | % of No. VC Investments | % of Amount of VC Investments |
|---|---|---|---|---|---|
| 25017 | Middlesex | MA | 116 | 10.7% | 19.7% |
| 6075 | San Francisco | CA | 113 | 10.4% | 8% |
| 36061 | New York | NY | 95 | 8.8% | 6.6% |
| 6081 | San Mateo | CA | 88 | 8.1% | 12.2% |
| 6085 | Santa Clara | CA | 78 | 7.2% | 9% |
| 6073 | San Diego | CA | 67 | 6.2% | 7.4% |
| 25025 | Suffolk | MA | 45 | 4.2% | 5.7% |
| 53033 | King | WA | 45 | 4.2% | 3.9% |
| 6037 | Los Angeles | CA | 43 | 4% | 2.6% |
| 6001 | Alameda | CA | 35 | 3.2% | 4.5% |
| 6059 | Orange | CA | 20 | 1.8% | 0.9% |
| 48453 | Travis | TX | 18 | 1.7% | 1% |
| 42003 | Allegheny | PA | 18 | 1.7% | 0.3% |
| 42101 | Philadelphia | PA | 17 | 1.6% | 0.3% |
| 27053 | Hennepin | MN | 13 | 1.2% | 1.2% |
| 9009 | New Haven | CT | 12 | 1.1% | 1.3% |
| 17031 | Cook | IL | 10 | 1% | 1% |
| | Total Obs. | 1083 | 100% | | |
| | Total No. of Counties | 118 | | | |

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