Friends versus Funding:

Unpacking the Dynamics of Social Connections and Staged Financing in VC Investment*

Fanqi Meng[†]

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Abstract

This empirical study investigates the determinants of staged financing in venture capital (VC) investments and assesses its influence on post-investment performance. By leveraging innovative proxies to measure outside opportunities and employing state-level non-compete agreements as a quasi-exogenous shock on outside opportunities, this research establishes entrepreneurs' outside opportunities as a key determinant of VC staged financing, providing the first empirical evidence in support of the hold-up hypothesis in VC investment. The findings reveal that higher outside opportunities are linked to increased staging, characterized by smaller investments per round and shorter round durations in the U.S. venture capital market. Furthermore, this research reconciles conflicting empirical findings in prior literature by highlighting a positive correlation between the number of financing rounds and entrepreneurial success when entrepreneurs face greater external opportunities. Lastly, this study enriches the venture capital and social finance literature by shedding light on the role of social connections in private market investments.

JEL Classifications: G15, G23, G24, G30, G32

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†Department of Finance, University of Melbourne, 198 Berkeley Street, VIC 3053, Australia. Correspondence: fanqim@student.unimelb.edu.au.

1 Introduction

The existing literature extensively documents the prevalent structure of venture capital (VC) financing through staged approaches (Sahlman, 1990; Lerner, 1994; Gompers, 1995; Gompers and Lerner, 1999; Hellman and Puri, 2001). However, despite numerous theoretical models attempting to address the determinants of VC staged financing, a definitive consensus remains elusive, especially within empirical analyses. Consequently, a gap persists in empirical research on this subject. This study seeks to empirically investigate whether the motivations driving VC staged financing are linked to the level of outside opportunities encountered by entrepreneurs and the subsequent implications for post-investment VC activities. To address this, innovative measures are employed to approximate the credibility of the outside opportunities confronted by entrepreneurs.

Why is this problem important and why do people care about it? To answer these questions, let's begin by examining the broader context of why VC financing is often staged. Hart (1991) emphasizes that, to maximize shareholder value, investors should ideally opt for a first-best investment strategy, meaning they invest whatever amount entrepreneurs request and patiently await returns. However, this strategy only thrives in scenarios where there is no asymmetric information between entrepreneurs and VC investors. Unfortunately, this ideal scenario rarely occurs in VC investments. Consequently, to bridge the information gap between VC investors and entrepreneurs, the most effective approach is to employ staged financing, which provides an answer to my second question regarding the reasons behind staged VC financing.

Prior literature (Gompers, 1995; Sahlman, 1990; Lerner, 1995; Hellman and Puri, 2000; Dahiya and Ray, 2012; Hsu, 2010; Tian, 2011) posits that information asymmetry arises from the uncertainty surrounding the fundamental value of entrepreneurial firms. Staged financing is seen as a substitute for intensified monitoring to address conflicts between entrepreneurs and VC investors. However, this study takes a different perspective, building upon Neher's (1999) model. Here, the hypothesis posits that asymmetric information is rooted in entrepreneurs' intentions (Neher, 1990; Hart and Moore, 1990; Ewens et al., 2016; Wang and Zhou, 2002; Cuny and Talmor, 2005; Bergemann and Hege, 1998; Noldeke and Schmidt, 1998; Landier, 2001). Entrepreneurs may strategically leverage information asymmetry by threatening to leave the firm for better career opportunities, thereby enhancing their bargaining power in negotiations with VC investors. In this context, entrepreneurs may intentionally withhold or utilize specific information to bolster their negotiating position. This form of information asymmetry can be perceived as a deliberate strategy employed by entrepreneurs to safeguard their interests and maximize their leverage in dealings with VC investors, constituting what is known as the managerial hold-up problem. This leads to my third question: does the hold-up problem indeed exist in VC investments?

I contend that it does, and I will illustrate this point with an anecdotal example. The case involving Abylaikhan Mukhamejanov and SkillSat serves as an illustrative example of the hold-up problem within the context of venture capital (VC) investment. In this scenario, Mukhamejanov, the founder of SkillSat, a burgeoning space technology startup with a track record of success, was enticed by the prospect of joining NASA, an esteemed entity operating within the same industry. Mukhamejanov's departure introduced potential risks to SkillSat's trajectory, granting him increased bargaining power during negotiations with VC investors. This practical scenario underscores the strategic leverage that founders can wield by leveraging external opportunities, compelling VC firms to recalibrate their strategies to retain pivotal talent and safeguard their investment interests. This case exemplifies how founders face potential outside opportunities and leave VC investors in potential investment failure, offering a classic illustration of the hold-up problem within the startup landscape.

Utilizing the Social Connectedness Index (SCI) as a gauge of the geographical structure within social networks, I devised two proxies grounded in SCI to gauge the potential external opportunities, encompassing both proactive and passive prospects, confronted by entrepreneurs. This approach was employed to examine the validity of the hold-up hypothesis.

On the academic front, while the hold-up hypothesis in VC investment has been acknowledged (Ewens et al., 2016), the lack of empirical evidence to substantiate this hypothesis persists. This gap in empirical support can likely be attributed to data limitations pertaining to the outside opportunities encountered by entrepreneurs. This study endeavors to empirically bridge this gap, determining the outside opportunities faced by entrepreneur is another factor driving VC staged financing. Employing the social connectedness index (SCI)[1] as a gauge of the ge-

[1] SCI is a measure of the extent to which people in different geographic locations interact with one another on social media. Precisely, it is based on the number of friendships between Facebook users in different locations and is intended to reflect the level of social connectedness between those locations. The SCI is calculated by Facebook's Data Science team and is publicly available as a dataset for research purposes.

ographical structure of social networks, I constructed two proxies, based on SCI, to measure the potential outside opportunities, including both passive and proactive outside opportunities, faced by entrepreneurs. The hold-up hypothesis suggests that higher outside opportunities would lead to a greater hold-up problem for VCs due to the high credibility of entrepreneurs threatening to leave the entrepreneurial firm and higher the bargaining powers retained by entrepreneurs, hence higher agency cost, resulting in a potential investment failure. VC investors tend to increase the number of financing rounds to mitigate the hold-up problem and decrease agency costs.

Through extensive empirical testing, my results support the hold-up hypothesis. Specifically, I find that when entrepreneurs face higher outside opportunities, including both proactive and passive outside opportunities, VCs tend to provide smaller investments per round, shorter round durations, more financing rounds, and a higher likelihood of additional rounds in the U.S. venture capital market. Overall, my findings provide empirical evidence in line with the hold-up hypothesis.

One notable concern within this study pertains to the presence of endogeneity issues inherent in the empirical analysis, particularly with regard to potential omitted variable situations arising from the utilization of the agency model as the basis for empirical testing. To address these concerns related to omitted variables and potential endogeneity, two distinct methods are proposed to establish causal effects. Firstly, a natural experiment framework is employed to mitigate potential endogeneity concerns. Specifically, the enforcement of noncompete agreements across different states is leveraged as an exogenous shock to the labor market, exerting a direct influence on individual and entrepreneurs' potential outside opportunities. These factors, in turn, influence the practices of venture capitalists within the private market. Secondly, two instrumental variables are constructed to proxy potential outside opportunities faced by entrepreneurs, and a two-stage least squares (2SLS) regression analysis is conducted. Additionally, alternative instrumental variables and alternative econometric approaches are explored to robustly address the issue of endogeneity, ensuring the validity of the causal effects.

A natural subsequent inquiry pertains to the post-investment performance of entrepreneurial firms subsequent to the reduction of agency costs. Previous literature has presented conflicting empirical results and hypotheses on the relationship between post-investment performance and the number of financing rounds raised by entrepreneurs. Gompers (1995) suggests that the number of capital infusions is positively correlated with post-investment performance, while Ewens et al. (2016) argue that the number of financing rounds is negatively correlated due to behavioral bias and opportunity costs throughout the fund's life cycle. My aim is to reconcile these competing hypotheses and provide empirical findings to better understand the effect of staged financing on post-investment performance.

My results align more closely with Gompers (1995), indicating a positive correlation between the number of financing rounds and the likelihood of entrepreneurial firms achieving success (e.g., IPO or acquisition) when entrepreneurs face higher outside opportunities. These findings support the hold-up hypothesis, suggesting that staged financing can mitigate hold-up/commitment problems, reduce agency costs, overcome moral hazard issues, and ultimately improve entrepreneurial performance.

In summary, drawing on agency models of VC investment, my empirical evidence supports the notion that the hold-up problem plays a significant role in the adoption of staged investment structures by VCs. While staging incurs costs such as extra efforts and legal fees, it serves to address hold-up issues that arise in each round of financing. Staged financing helps mitigate commitment problems, align the goals and incentives of entrepreneurs and investors, reduce agency costs associated with information asymmetry and moral hazard, and improve venture performance. Moreover, staged financing provides flexibility to adjust investment levels based on the performance and effort of the entrepreneur, mitigating commitment and renegotiation problems and reducing the risk of sub-optimal investments, decreasing investment failures.

My paper makes contributions to several streams of literature. Firstly, it adds to the venture capital literature from two key perspectives. On one hand, it fills the empirical gap in the field of VC investment structure. To the best of my knowledge, this study is the first to empirically identify the cause of staged financing, which can be attributed to the hold-up hypothesis, using a novel proxy. Previous studies in this area have predominantly focused on theoretical and computational analyses, as evidenced by works such as Neher (1999), Wang and Zhou (2002), Dahiya and Ray (2012), Hsu (2010), and Giudici and Paleari (2010). On the empirical side, there are only a few studies that establish a connection between effective monitoring and staged capital infusion. Gompers (1995) examines how agency and information problems impact the structure of staged VC investments using industry-level proxies. Tian (2011) explores the relationship between effective monitoring and the structure of VC investments based on location information.

Ewens et al. (2016) acknowledge the existence of hold-up problems but do not conduct empirical tests. This study advances this line of inquiry by empirically testing the hold-up hypothesis proposed in the existing theoretical literature and demonstrating that staged financing in VC investments could be attributed to the outside opportunities faced by entrepreneurs.

On the other hand, my results contribute to the literature examining determinants of venture capital performance. Gompers (1995) investigates how agency and information problems influence the structure of staged VC investments. Hall and Woodward (2010) examine how reputation impacts the selection of VC firms. Groh et al. (2010) explore how VC reputation affects the performance of portfolio firms. I provide empirical evidence that in addition to reputation, due diligence, experience, and expertise, the outside opportunities of entrepreneurs significantly affect the outcomes of entrepreneurial firms.

Moreover, my findings provide a reconciliation between two contrasting empirical analyses concerning the relationship between the number of financing rounds and the post-investment performance of entrepreneurial firms. Gompers (1995) posits a positive correlation, suggesting that an increased number of capital infusions is associated with improved post-investment performance. In contrast, Ewens et al. (2016) argue for a negative correlation, attributing it to behavioral bias and opportunity costs throughout the fund's life cycle. The results of my study align more closely with Gompers (1995), revealing a positive correlation between the number of financing rounds and the likelihood of entrepreneurial firms achieving success, contingent upon entrepreneurs facing higher outside opportunities.

Secondly, my work contributes to the social finance literature. The role of social interactions in measuring various economic outcomes is a relatively new and rapidly growing area. Bailey et al. (2017) emphasize the role of social connectedness in shaping individual behavior and social outcomes. Kuchler et al. (2018) examine the impact of technological innovation on resource allocation and long-term economic growth using social interactions. Kuchler et al. (2022) demonstrate how social interactions affect the portfolio allocation of institutional investors. Bailey et al. (2020) examine the economic effects of social networks on the housing market. My study extends this literature by highlighting the role of social interactions in the private market and labor market as well as its implications in these areas.

The remainder of the paper is organized as follows: Section 2 presents the hypotheses development. Section 3 discuss the proxy measurement, Section 4 introduces the sample, variable construction, and descriptive statistics. Section 5 discusses the results of hypothesis testing. Section 6 presents the implications of the hypotheses. Finally, Section 7 provides the concluding remarks.

2 Hypotheses Development

In this section, I will discuss the development of testable empirical hypotheses based on the current theoretical models.

2.1 Hold-up Hypothesis

According to the literature (Ewens et al., 2016; Landier, 2003), staged financing in venture capital (VC) investments offers benefits for both venture capitalists and entrepreneurs but also introduces potential hold-up costs. These costs are more pronounced in VC investments due to the inherent information asymmetry. One contributing factor is the inalienability of human capital, which is not tied to the entrepreneur's firm due to informal contracting (Hart and Moore, 1994; Neher, 1999). Despite the importance of human capital in VC investments, its impact has often been overlooked.

On one hand, entrepreneurs invest their efforts into the firm and specialize their human capital, creating an opportunity cost if the firm fails. Both entrepreneurs and VCs share the goal of firm success, thereby mitigating agency costs (Fluck et al., 2004). On the other hand, intangible assets such as human capital are as valuable as tangible assets. Human capital is hard to replace and critical for realizing the venture's full potential (Hart and Moore, 1994; Neher, 1999). However, the entrepreneur retains the right to exit the venture, leading to commitment/hold-up problems (Bigus, 2004). Staged financing addresses these issues by treating human capital as collateral, protecting the VC's claim and reducing the entrepreneur's incentives to leave the firm (Cuny and Talmor, 2005). Additionally, staging enables VCs to gradually learn the project's value, encouraging entrepreneurs to exert higher effort and not divert subsequent capital (Noldeke and Schmidt, 1998; Neher, 1999; Landier, 2001). Thus, the severity of the hold-up problem determines the number and size of financing rounds needed (Landier, 2003; Chemmanur et al., 2009).

Practical hold-up issues also arise in VC investments, as indicated by Ewens et al. (2016).

VC firms often add additional rounds of funding to keep promising investment opportunities private. This suggests low information asymmetry between entrepreneurs and VCs and highlights the influence of commitment problems, such as hold-up issues, on the decision to opt for staged financing.

In summary, the testable predictions of the ***hold-up hypothesis*** can be summarized as follows: the severity of the hold-up problem, represented by the outside opportunities faced by entrepreneurs, is positively correlated with the number of financing rounds, smaller investment amounts per round, a higher likelihood of additional rounds, and shorter durations between successive financing rounds.

Staged financing also has a significant impact on the post-investment performance of entrepreneurial firms. Human capital serves as an instrument that balances the conflicting interests in the venture financing process and future shareholder returns. Lower hold-up problems lead to better subsequent outcomes for entrepreneurs, as they face fewer outside opportunities and require fewer additional financing rounds, resulting in lower agency and staging costs and better post-investment performance. Conversely, when the hold-up problem is severe, more financing rounds are needed to mitigate the agency problem and prevent investment failure. In this case, increased financing rounds can alleviate the hold-up problem and contribute to better subsequent performance. In summary, the empirical behavior regarding post-investment performance indicates a positive correlation between the number of capital infusions and entrepreneurial firm performance when the hold-up costs are high, i.e., when entrepreneurs face significant outside opportunities.

3 Measurment

The inclusion of the Social Connectedness Index (SCI) as a proxy in this analysis serves several important purposes.

First, it's important to establish that SCI serves as a reliable measure for assessing one's external opportunities. Drawing inspiration from Granovetter's sociological work "The Strength of Weak Ties" (1973), it becomes evident that weak ties within social networks are particularly efficacious in facilitating job opportunities and career progression. Granovetter, 1973 emphasizes that weak ties, characterized by their diversity, offer access to novel information and resources unavailable within closely-knit strong tie networks. Unlike strong ties, which often consist of individuals from similar social circles and are less inclined to disseminate novel job information, weak ties are instrumental in revealing non-publicized job openings and introducing individuals to fresh contacts and prospects. Importantly, Granovetter notes that weak ties are naturally formed through shared activities or acquaintances rather than being deliberately cultivated. This aligns precisely with the relationships fostered within geographically structured social networks, such as the SCI based on Facebook. Thus, the SCI data emerges as an optimal tool for gauging the external career opportunities encountered by entrepreneurs, given its resonance with Granovetter's observations on weak tie networks.

Davern and Hachen (2006) expand upon the concept of weak ties and assert that social networks contribute to job mobility through two key mechanisms. Firstly, they facilitate access to diverse sources of information about job openings. A well-connected network can enhance the dissemination of information within labor markets, pertaining to available job opportunities and potential candidates, thereby promoting increased job mobility. Secondly, these networks provide access to non-redundant sources of influence. Contacts who are not interconnected (i.e., contacts who do not know each other) offer distinct resources and information, elevating the prospects of securing better job prospects.

The geographic structure of social networks aligns seamlessly with the prerequisites of heightened job mobility, particularly with regard to outside opportunities. Friends on platforms like Facebook could be categorized as acquaintances, distinct from close-knit social circles, potentially spanning various industries, and locations, and sharing diverse information. Consequently, the Social Connectedness Index (SCI) data proves to be an ideal metric for quantifying the outside opportunities faced by entrepreneurs.

Moreover, Agnihotri et al. (2020) have observed that individuals are actively utilizing social media platforms, particularly Facebook, as a means to explore new career prospects, as evidenced by survey results. These attributes collectively render SCI a suitable metric for gauging the external opportunities available to an individual.

To assess whether this data is apt for measuring the outside opportunities of entrepreneurs, insights from Shane and Cable (2002) are instructive. Their research reveals that entrepreneurs, much like individuals in conventional job searches, seek potential job openings through the use of referrals, a fact established through survey-based interviews. Fedyk and Hodson (2023) further corroborate this assertion by demonstrating that the proportion of individuals who transitioned from Lehman Brothers to entrepreneurship is significantly higher than those from comparable banks, spanning various roles including analysts and associates. This empirical support fortifies the notion that entrepreneurs indeed explore employment opportunities through weak ties. Consequently, the credibility of employing SCI as a metric to assess outside opportunities is reinforced.

Secondly, it aligns with the hold-up hypothesis, as suggested in the literature, where a suitable proxy should capture the potential outside opportunities available to entrepreneurs. Social connectedness fits well within this criterion. The SCI not only measures the geographic structure of social network between the entrepreneur and investors but also considers the connections between the entrepreneur and other peers within their network. Drawing from relevant theories (Neher, 1999; Ewens et al., 2016; Cuny and Talmor, 2005; Landier, 2003), I interpret the proxy as follows: if the level of social connectedness, which represents the potential outside opportunities faced by entrepreneurs, is high, it indicates a more severe hole-up problem. This is because the parties involved are more likely to be connected with other potential employers and peer entrepreneurs, thereby making the threats of leaving the entrepreneurial firm more credible. Consequently, an increased number of financing rounds can help mitigate this hold-up problem. Conversely, if the level of social connectedness is low, it suggests a less severe hold-up problem, as the parties are more likely to have established a trust-based relationship with a lower risk of defection.

Thirdly, the lack of empirical research on the hold-up hypothesis can be attributed to certain assumptions made in theoretical models (Neher, 1999; Cuny and Talmor, 2005; Landier, 2003), which assume that VC investments are made with less uncertainty and that investors and entrepreneurs possess symmetric information regarding the project. Social connections can aid in decreasing the opacity of confidential information, such as the quality of entrepreneurial firms, which aligns more closely with the assumptions of these models. Moreover, social media and social networks play a significant role and can increase the costs associated with defection, thereby reducing the extent of asymmetric information.

Lastly, utilizing the SCI as a proxy significantly mitigates endogeneity problems. Unlike other proxies employed in empirical studies, the SCI cannot be modified endogenously by either of the parties involved. It is exogenously calculated based on the geographic locations of each party. Furthermore, the social connectedness index takes into account not only geographic proximity but also incorporates demographic characteristics such as education level, wealth, life expectancy, migration patterns, and patent citation information (Bailey et al., 2017). This helps alleviate concerns related to omitted variables to a significant extent.

4 Data

4.1 Data and Summary Statistics

4.2 Venture Data

I obtained VC investment data from the Preqin dataset, which provides deal-level investments made by VC investors to their entrepreneurial firms from 1969 to 2022. The primary focus of my analysis centers on investment activities that took place within the United States. Within my sample, I have identified a total of 119,344 unique investment deals involving 66,428 entrepreneurial firms whose headquarters are located in the United States. These firms have received VC/private equity (PE) financing after 2016. Due to the data limitations and time invariant nature of the social connectedness index, the baseline analysis only focus the VC investment deals occurred after 2006. Specifically, I only include the entrepreneurs who received their first VC investment after 2006. Moreover, the analysis encompasses a comprehensive geographic scope, covering 1,041 counties across the United States.

The Preqin dataset offers comprehensive and detailed information on investments, encompassing various aspects such as the number of investors, investor location, investor names, investment amounts for each round, investment dates, exit amounts, and the type of exit for each entrepreneurial firm. However, it should be noted that Preqin classifies mergers into several distinct exit types, including Trade Sale, Sale to GP, and Unspecified Exit. In order to enhance the analysis and capture a more accurate representation of mergers, I introduce additional classifications based on the firm's exit value in relation to the amount of investment received from VC financing. Specifically, I classify a firm as a successful merger if its exit value exceeds the total investment received from VC/PE. This accounts for cases where Preqin may not have explicitly categorized a firm as a merger. Similarly, I apply a similar logic to identify write-off firms. In addition to the firms already marked as write-offs in the dataset, I classify a firm as a write-off if its exit value is lower than the total amount of investment it received from VC/PE. The process leaves a total of 6,250 firms meet the criteria for success, specifically characterized by an exit type of either IPO or merger, while being located within the United States in the sample period.

The address information for both entrepreneurial firms and VC firms is obtained from the Preqin dataset. However, it should be noted that Preqin provides location information for entrepreneurial firms at the state-city level. In order to align with the county-level social connectedness index, a mapping process is conducted to associate each city-state with its corresponding county-state. To facilitate this mapping process, a publicly available dataset provided by the United States Census Bureau is utilized. This dataset allows for the linkage of city-state information to the corresponding county-state information. [2]

Furthermore, the dataset includes comprehensive coordinate information, specifically latitude and longitude data, for each location. Leveraging this coordinate data, I employ a calculation method [3] to determine the geographic distance between each pair of locations. The sample includes a total of 64,118 distinct individual firms and 274,747 pairs consisting of entrepreneurial firms and their corresponding private investors, where distance information is available.

Moreover, using the comprehensive information provided by the Preqin dataset, I constructed a set of characteristic variables for both venture capital firms (VCs) and entrepreneurial firms. These variables contain various aspects such as the number of syndicated VCs involved, dummy variables indicating different exit types, the total amount of investment raised by firms, and more. In order to capture the dynamics of the financing process, I derived the variable "number of financing rounds" based on the investor, deal investment, and investment date information. This variable reflects the count of financing rounds that the entrepreneurial firm has successfully raised. To further investigate the distinct impact of inside and outside rounds, I formulated separate variables for inside rounds and outside rounds. These variables indicate whether the investors had previously invested in the firm before the current round. Inside

[2] The mapping dataset can be freely downloaded from the following source: [https://simplemaps.com/data/us-cities].

[3] To calculate the geographic distance between two parties, I apply the formula based on spherical geometry and trigonometric math functions. Namely, I convert the latitude and longitude from decimal degrees to radians by dividing the coordinates by $180/\pi$, or approximately 57,296. Then calculate the mileage between two parties in the following formula, based on the radius of the Earth is 3963 miles: $\textit{Geographic Distance}_{i,j} = 3963 \times \text{Arccos}\left[\sin(\text{Lat}_i) \times \sin(\text{Lat}_j) + \cos(\text{Lat}_i) \times \cos(\text{Lat}_j) \times \cos(\text{Long}_j - \text{Long}_i)\right]$ Where Lat_i and Long_i are the coordinate for VC investors, and Lat_j and Long_j are coordinate for entrepreneurial firms.

rounds are measured continuously to capture the ongoing investment by existing investors.

4.3 Industry and Macroeconomic Data

Given the unavailability of accounting data for private companies, I accessed industry-level accounting information for entrepreneurial firms from the Compustat database. As the Preqin dataset did not include the Standard Industrial Classification (SIC) number, I manually merged the industry information provided in Preqin with the corresponding industry data found in Compustat manual book. Subsequently, I computed the average industry-level measures for asset tangibility (the ratio of tangible assets to total assets), growth opportunities (market value of equity to book value), and research intensity (the ratio of R&D expenditures to total assets) at the year level. To ensure consistency and accuracy, the data were matched by year and industry to the firm and deal date information provided in Preqin, to measure the entrepreneurial firms' financial characteristics in relation to their investment activities.

4.4 Social Connectedness Index Data

To quantify the level of social connectedness between U.S. counties, U.S. counties and countries, and countries themselves, I utilize the Social Connectedness Index (SCI) introduced by Bailey et al. (2018). This index leverages anonymized data on social media activity to measure the extent of connections between recorded locations. By analyzing the registered information and major activities of active social media users, individuals are assigned to specific locations.

Empirical studies conducted by Duggan et al. (2016) and Kuchler et al. (2021) have demonstrated the validity of using the social media-based index as a suitable proxy for measuring real social connections between two locations. Notably, platforms such as Facebook predominantly serve individuals who are acquainted with real life, and the demographic characteristics of friends on such platforms tend to exhibit notable similarities.

Formally, the *Social Connectedness Index* between county i and j is constructed as follows:

$$Social\ Connectedness\ Index_{i,j} = \frac{FB\_Connections_{i,j}}{FB\_Users_i \times FB\_Users_j} \tag{1}$$

where FB_Users_i and FB_Users_j are the number of social media users in counties i and j, and $FB\_Connections_{i,j}$ the total number of Facebook friendship connections between individuals in the two locations.[4] The index I used in this study has already been scaled by population and other demographic information in each locations, so the index measures the relative probability of connections link between users in two different locations.

4.5 Summary Statistics

Figure 1 illustrates the time-series trends in the number of entrepreneurial firms receiving private market investment and the total investment amount in the United States from 1990 to 2021. Over the past two decades, there has been a significant increase in the number of firms attracting private market investment, rising from 134 firms in 2000 to 3,095 firms in 2021.

In the online appendix, I provide a geographic analysis of the distribution of entrepreneurial firms and venture capital/private equity (VC/PE) investors across the United States throughout the sample period spanning from 1969 to 2022. Notably, the number of entrepreneurial firms surpasses that of VC/PE investors, and their geographical distribution appears to be more scattered. This observation suggests the presence of potential hold-up problems in post-investment activities in post-investment venture activities.

Table 1 presents an overview of venture capital financing in the United States from 1995 to 2021. The number of funding rounds conducted by venture capitalists exhibits a positive correlation with the number of entrepreneurial firms receiving funding. The data analysis reveals notable trends in venture capital and private equity financing. In 2010, a total of 1,374 entrepreneurial firms received a substantial amount of 227,939.4 million in VC/PE financing. This represents a remarkable increase of nearly 16 times in terms of funding amount and 37 times in the number of firms compared to the private market in 1995. It is worth noting that the data coverage appears to improve after 2000, possibly reflecting the enhanced completeness of the Preqin dataset over time or a modest size of venture capital investments before 2000. The data shows that there are 1374 entrepreneurial firms received a total amount of 227939.4 million dollars of VC/PE financing in 2010, almost 16 time in amount and 37 time in quantity to the private market in 1995. Furthermore, the average funding amount invested in individual firms has experienced a significant decrease since the "tech bubble", suggesting the presence of financial constraints faced by venture capital investors. On the other hand, the average number

[4]The Social Connectedness Index data is available at http://data.humdata.org/dataset/social-connectedness-index

of successful funding rounds raised by each firm has remained relatively constant over the past 20 years.

Table 2, provides insights into the outcome distribution for firms that received venture capital financing. It is important to note that the table only includes firms that reported their exit type in the Preqin dataset. For firms that did not report the exit type or indicated an "Unspecified Exit," I categorize them either as firms undergoing liquidation or remaining private or as firms involved in a merger based on the investment value and exit value reported in the dataset. Firms that neither reported the exit type nor specified the exit value are excluded from the analysis. In the United States, the IPO rate for VC-backed entrepreneurial firms has shown a substantial decrease since 1998, while the rate of successful mergers has increased, resulting in a relatively constant rate of unsuccessful outcomes for VC-backed firms. To illustrate, let's consider the year 2012, where 63 firms successfully went public, accounting for a 4.61% IPO rate for that particular year.

The examination of funding structure by outcome helps determine whether venture capitalists periodically assess a firm's prospects. Table 3 further supports this notion by revealing that the number of financing rounds tends to be higher for firms that go public (IPO) compared to firms that are acquired or liquidated/remain private. Moreover, firms that are acquired tend to have more financing rounds than those that are liquidated or remain private. Interestingly, in 2012, we observe extreme cases wherein the average number of financing rounds for IPOed firms was 5, contrasting with an average of 2.356 rounds for firms that were either liquidated or remained private. These findings indicate that venture capital and private equity investors strategically stage capital infusions based on the milestones achieved by entrepreneurial firms. All findings are further supported by the global data, which are provided in the online appendix and yield similar results.

Table 4presents the key summary statistics for the social connectedness index, including county to the county level, county-to-country level and, country-to-country level, distance, VC firm characteristics, entrepreneurial firm characteristics and, VC investment characteristics. The county level social connectedness index is defined as the number of Facebook links between firms headquarter's county location and that of a VC firm's, scaled by the product of the populations in these two locations (multiplied by 10^{12}). Distance is measured by the associated geographic distance. The maximum of SCI in county level is 462,981,391 occurs when both VC investors and entrepreneurial firms located in King county, Washington State. While the minimum of SCI in county level is 1 indicating that the pair of the location did not have any Facebook users, or no social connections between the two locations. The distribution of social connectedness index variables is right-skewed. Economically speaking, the differences between 1 and 100 are huge but the differences between 10,000 and 10,100 are small, so to minimize the magnitude difference, I take natural logarithm on both key and control variables. With logarithms, the distribution of each of the variables looks more symmetric.

Additionally, the table presents summary statistics pertaining to geographic distance, as well as characteristics of both VC and entrepreneurial firms. Upon applying logarithmic transformation, the distribution of geographic distance closely approximates that of the Social Connectedness Index (SCI). On average, VC firms receive 3.52 rounds of financing, with an average of 1.6 rounds classified as inside rounds (follow the definition in (Ewens, et al., 2016)). Within the United States, approximately 37.28% of entrepreneurial firms have received additional rounds of VC financing. The average duration between the next financing round and the previous financing round is 19.04 months. The average age of entrepreneurial firms at the time of their first VC financing is 2.14 years, and they typically attract an average of 5.05 syndicated VC investors. Each entrepreneurial firm, on average, receives a total investment of $288.55 million dollars, with the initial round of investment amounting to approximately $94.44 million dollars. Moreover, the industry-level asset tangibility ratio for entrepreneurial firms stands at 17.2%, the R&D-to-assets ratio is 18.3%, and the market-to-book ratio is 0.508.

5 Empirical Analysis

This section presents the empirical findings regarding the determinants of VC staged financing. In particular, I investigate the impact of outside opportunities of entrepreneurs on staged financing, including the number of financing rounds, the number of inside investor financing rounds, the duration between successive financing rounds, the investment amount per round, and the likelihood of raising an additional round.

5.1 Baseline Results on Hold-Up Hypothesis

5.1.1 Outside Opportunities Measured using Industry Average

Despite using the social connectedness index (SCI) as a measure of outside opportunities of entrepreneurs to examine the hold-up hypothesis, I acknowledge that I am not utilizing the SCI measure based on the headquarters location between entrepreneurial firms and VC investors. In order to capture credible threats of entrepreneurs leaving the firm, I propose two types of SCI measurements to assess outside opportunities. These outside opportunities can be categorized into two types: actively seeking a new job and passively receiving job offers from headhunters or other companies within the same industry. Typically, entrepreneurs are less likely to actively seek job opportunities themselves because of the level of effort they put in the firm and substantially high opportunity cost it might occur if they walk away, and instead, they are more likely to receive passive offers based on their reputation and capabilities from headhunters or other firms in the same industry. The likelihood of receiving such offers from headhunters or other firms is positively correlated with the social connections between the entrepreneurs and these entities. Hence, the first type of outside opportunities can be proxied by the average social connectedness index between the headquarter locations of entrepreneurial firms and those of other firms. The calculate formula as shown below

$$SCI_{industry\ average,EN} = \frac{\sum_{i=1}^{N} SCI_{i,EN}}{N} \tag{2}$$

where i represents each firm within the same industry as entrepreneurial firm A, and $SCI_{i,EN}$ denote the social connections, measured by the headquarter locations, between firm i and entrepreneurial firm A. The proxy can be interpreted as follows: a higher social connectedness index indicates a greater chance for entrepreneurs to receive job offers from similar firms.

The baseline regression model for hold-up hypothesis as shown below:

$$\begin{aligned} Number\ of\ Financing\ Round_i &= \beta_1 Outside\ Opportunities_i + \beta_2 X_i + \beta_3 Y_j \\ &+ Year_{FE} + County_{FE} + Industry_{FE} + VC_{FE} + VC * Industry_{FE} + \epsilon_{i,j} \end{aligned} \tag{3}$$

The dependent variable in this study is the number of financing rounds raised by entrepreneurial firms, while the main explanatory variable of interest is the outside opportunities faced by entrepreneurs.

The regression results, as presented in Table 5, employ the industry average social connectedness index (SCI) as the primary explanatory variable to examine the hold-up hypothesis. In addition to the main explanatory variable, I incorporate a comprehensive set of control variables, including the number of VC investors, characteristics of entrepreneurial firms and VC firms, industry averages, outcome dummy variables, and various fixed effects. Robust standard errors, accounting for heteroskedasticity, are reported in parentheses.

Consistent with the hold-up hypothesis, which posits that VC investors increase the number of financing rounds when outside opportunities are high, the baseline regression results in column 1 reveal that the coefficient estimates of the industry average SCI are positive and statistically significant at the 0.1% level. This suggests that a higher social connectedness index between the headquarters location of entrepreneurial firms and other firms in the same industry, indicating a more severe hold-up problem for entrepreneurs, is associated with a larger number of financing rounds. Specifically, a 1 unit increase in the industry average SCI leads to a 0.185 increase in the number of financing rounds for entrepreneurs in the baseline regression.

To address potential omitted variable concerns, I introduce additional control variables and fixed effects in columns 2 through 6. Column 2 incorporates control and year-fixed effects to capture time-varying market effects. To account for the influence of investors, column 3 includes VC investor fixed effects, ensuring that the results are not driven by location-specific characteristics that may affect the outcome of the analysis or by characteristics that make VC firms in socially connected counties more likely to attract entrepreneurial firms on average. Additionally, in column 6, I introduce VC investor * industry fixed effects to capture the effects of strategically locating in socially connected regions that align with investors' investment objectives. While these fixed effects account for some of the variation and magnitude in the analysis, the coefficient estimates capturing the effect of social connectedness on staged financing remain unchanged and statistically significant, with economically meaningful implications. These findings indicate the existence of the hold-up hypothesis in VC-staged investments in the United States.

Regarding the control variables, the analysis aligns with the monitoring hypothesis, indicating that physical distance yields inconsistent results in relation to the outcome of VC-staged financing. This further emphasizes that geographic proximity is not an optimal or reliable proxy for testing either the monitoring hypothesis or the hold-up hypothesis. Furthermore, the findings reveal a positive relationship between the number of investing VC firms and the number of VC financing rounds. Additionally, the amount of investment in the first round is negatively correlated with the number of financing rounds. These results are consistent with previous studies by Gompers (1995) and Tian (2011), suggesting that firms in industries with more tangible assets tend to receive fewer rounds of financing due to higher liquidation value and firm value. However, the analysis does not provide conclusive evidence regarding the impact of the industry market-to-book ratio and industry R&D ratio on VC staged financing.

5.1.2 Outside Opportunity Measured using Industry Average SCI on other aspects of VC-Staged Financing

To comprehensively analyze the hold-up problem in VC-staged investment, I conducted further investigation into how the industry average social connectedness index (SCI) impacts various aspects of VC-staged financing, including the investment amount per round, round duration, additional rounds following the first round of financing, and the number of inside rounds of financing.

Table 6 presents the results of how the industry average level of SCI influences the investment amount per round. The dependent variable is the natural logarithm of the round size in millions of US dollars. Since the number of VC investors and their respective investment amounts vary at each round of financing, each observation in this regression represents each entrepreneurial firm and investor at each round. However, due to incomplete investment amount information in the dataset from Preqin, observations without this information were excluded. Robust standard errors, accounting for heteroskedasticity, are reported in parentheses, consistent with previous analyses.

The results in the table consistently indicate that the coefficient estimates of the industry average level of social connectedness index (SCI) are negative, statistically significant, and economically meaningful across all specifications with different control and fixed effects. These findings provide confirmation for the hold-up hypothesis, which suggests that a higher social connection between entrepreneurs and other firms in the same industry leads to a decrease in the investment amount per round made by VC investors. This can be attributed to the fact that an increased SCI between entrepreneurs and other firms enhances the likelihood of entrepreneurs being offered job opportunities by other entities, thereby making the threat of leaving the firm more credible. Consequently, VC investors become less secure in committing a large amount of capital in each financing round.

Specifically, the baseline regression results presented in column 1, without any control and fixed effects, indicate that a 10% increase in the industry average level of SCI results in a 14.6% decrease in the investment amount per round. Even after incorporating controls for industry clustering and the effects of VC investors' location preferences, the coefficient associated with the hold-up problem remains unchanged and statistically significant. The elasticity persists at the 8% level even after accounting for the variation captured by the fixed effects.

Additionally, in line with previous research Fluck et al. (2004), the number of syndicated VC investors exhibits a positive correlation with the investment amount in each round of VC-staged financing. Overall, the results regarding the investment amount per round align with the hold-up hypothesis, indicating that when entrepreneurs have greater outside opportunities, VC investors reduce the investment amount per round to mitigate the VC hold-up problem.

Table 7 presents the regression results examining the impact of the industry average social connectedness index (SCI) on inside rounds of financing conducted exclusively by VC investors who had previously invested in the entrepreneurial firms. Ewens et al. (2016) highlight the significance of inside investors, who possess superior information due to their previous investments and can provide valuable insights into analyzing hold-up problems. Inside VC investors are particularly relevant to the hold-up theory, which assumes no investment uncertainty and aligns well with the characteristics of inside investors.

The table demonstrates that the coefficient estimates of the industry average SCI are consistently positive, statistically significant, and economically meaningful across different specifications with varying control variables and fixed effects. These findings align with the results reported in Table 6, which utilized the total rounds as the dependent variable, albeit with slightly lesser magnitude. According to the coefficient estimate presented in the baseline regression shown in column 1, a one-unit increase in the industry average social connectedness index between entrepreneurial firms and other firms in the same industry leads to a 0.0815 increase in inside rounds. These results are consistent with and support the implications of the hold-up hypothesis, indicating that higher outside opportunities faced by entrepreneurs result in a greater number of rounds provided by inside VC investors.

Interestingly, contrary to the previous analysis, the number of syndicated VC investors shows a negative relationship with inside rounds of financing, which may be attributed to reduced under-provision of effort and increased continuity efficiency.

To save space, the tests examining the effects of industry average SCI on additional rounds and round duration are presented in the online appendix. Overall, the results consistently align with the hold-up hypothesis. Higher outside opportunities, as proxied by the industry average SCI between entrepreneurial firms and other firms in the same industry, correspond to a more severe hold-up problem. To mitigate this problem, VC investors increase the number of financing rounds, shorten the duration between successive rounds, and reduce the investment amount per round to protect themselves against potential failures of entrepreneurial firms. These findings provide evidence consistent with the hold-up hypothesis.

5.1.3 Outside Opportunity Measured using Mean SCI

While the likelihood is relatively low, there may still be situations in which entrepreneurs actively seek outside opportunities. In the event of disagreements between entrepreneurs and VC investors, such as issues regarding future projects, allocation of shares in subsequent financing rounds, or control over board seats, entrepreneurs may contemplate leaving the firm they founded and seeking alternative employment. In such cases, entrepreneurs are likely to begin their job search locally, where they currently reside, or in places they are familiar with, leveraging their extensive connections and professional relationships. One of the key locations with professional connections for entrepreneurs is the headquarters location of the VC investors who have made investments in their firms. After VC investments are made, entrepreneurs may frequently visit the VC investors' location, establishing professional connections with local firms and investors through their existing investors. Consequently, the second most connected location for entrepreneurs is often the location of VC investors.

To capture the proactive outside opportunities available to entrepreneurs, I employ the average social connectedness index (SCI) between the local location of the entrepreneurial firm itself and the headquarters locations of both entrepreneurial firms and VC investors. As shown in below formula

$$SCI_{mean,EN} = \frac{SCI_{EN} + SCI_{VC,EN}}{2} \tag{4}$$

A higher SCI indicates a greater likelihood for entrepreneurs to find job opportunities, thereby enhancing the credibility of their threat to leave the firm. The regression results, presented in Table 8, utilize the average SCI as the main explanatory variable to test the hold-up hypothesis. The findings are consistent with those examining the passive outside opportunities faced by entrepreneurs. The coefficient estimates for the average SCI between the headquarters locations of entrepreneurial firms and that between entrepreneurial firms and VC investors are positive, statistically significant, and economically meaningful. Specifically, a 1 unit increase in the average SCI, capturing proactive outside opportunities, leads to a 0.0696 increase in the number of financing rounds, as shown in the baseline regression in column 1 of Table 9. These coefficient estimates remain robust even after incorporating various control variables and fixed effects. The statistically significant and economically meaningful findings confirm the hold-up hypothesis, suggesting that higher outside opportunities and credible threats of leaving prompt VC investors to increase the number of financing rounds to mitigate the hold-up problem.

Consistent with previous analyses, the number of syndicated VC investors is positively related to the number of VC financing rounds. Additionally, the tangible assets of the industry exhibit a negative relationship with the number of capital infusions, attributed to the association between tangible assets and liquidation value and firm value.

To save space, the results pertaining to the effect of the average SCI, measuring proactive outside opportunities, on other aspects of VC-staged financing are presented in the online appendix. In the untabulated reports, I also conduct Poisson maximum likelihood regressions for all the aforementioned tests to address potential nonlinearity issues between VC-staged financing and the social connectedness index. The results align with those obtained from the OLS regressions.

In summary, VC-staged financing, where investment conducted in the United States, is consistent with the hold-up hypothesis, indicating that VC investors strategically stage capital infusions to mitigate the hold-up problem arising from potential opportunistic behavior by entrepreneurs. Specifically, I find that higher levels of both proactive and passive outside opportunities lead to an increased number of capital infusions by VC investors, a higher number of inside capital infusions exclusively by previously invested VC investors, a shorter duration between successive rounds, and smaller investment amounts per round. However, I did not find evidence supporting the monitoring hypothesis in the context of VC-staged financing.

5.2 Identification Strategy

5.2.1 Natural Experiment

Theoretical investigations of VC staged financing commences with a principal-agent framework, encompassing distinct characteristics of the principal (VC investor), agent (Entrepreneur), and the specific attributes of the VC staged financing itself. In order to empirically examine the factors influencing the number of capital infusions, a regression model is constructed using observable characteristics of VC investors, entrepreneurs, and the investment. It is essential for the regression model to accurately account for all relevant characteristics of the three parties and employ precise measures rather than proxies to quantify the quantity and quality of these characteristics. Nevertheless, empirical testing encounters substantial difficulties in capturing all relevant characteristics, as certain characteristics may be unobserved, partially observed, or observed with error, thus giving rise to endogeneity issues in the empirical regression modeling process (Ackerberg and Botticini, 2002).

A particularly challenging aspect of my study involves the examination of the outside opportunities faced by entrepreneurs, given the potential endogeneity of outside opportunity measures and the possibility of omitted variables. A key challenge lies in disentangling the causal effects of outside opportunity from potential confounding factors, as unobserved variables that influence the severity of geographic structure of social connections, the measure of outside opportunities may also impact the number of rounds raised by VCs. This assumption is not easily verifiable and has the potential to affect the causal effect that I claim. To address these challenges, I employ a natural experiment identification strategy that involves the careful selection of a control group and the utilization of the staggered diff-in-diffs estimation method.

5.2.2 Research Design to Build the Control Group

Human capital is inherently distinct from other forms of capital in that firms typically do not exert direct control over employees in most companies, including both public and private enterprises (Becker 1962; Hart and Moore 1994). The loss of key human capital can result in significant economic damage attributed to the inalienable human capital possessed by these key employees (Kini et al., 2020; Neher, 1999; Hart and Moore, 1994). To mitigate the potentially adverse effects arising from the job mobility associated with human capital, common law, such as non-compete agreements (NCAs), was introduced to safeguard firms from such scenarios. These NCAs are governed by state-level employment laws and are often enforceable within specific geographic regions, typically corresponding to the company's headquarters state. By restricting an employee's capacity to work for a competitor or establish a competing business within the same industry, NCAs can curtail the spectrum of potential job opportunities, both in terms of geographical scope and timeframe. Consequently, employees may encounter difficulties in seeking alternative employment or pursuing entrepreneurial endeavors in their chosen field, resulting in limitations to their external opportunities and a reduction in bargaining power. The impact of this law extends to individuals within the geographic regions, including entrepreneurs operating within these areas. If the hold-up hypothesis is valid and the causal effect is upheld, the diminished outside opportunities faced by entrepreneurs subsequent to the implementation of this common law will translate into a decreased number of financing rounds in the private VC market.

Specifically, the enforcement of NCAs is subject to state-level employment laws, and the degree of enforceability of these NCAs varies across states and has undergone changes over time in certain states. States differ in terms of the duration for which an NCA remains enforceable, the extent of enforceability within each state, the coverage of NCAs signed by employees, and other related factors. In line with contract theory, which underscores the significance of enforceability (Tirole 1999; Baker et al., 2002; Jackson 2011), the limited geographical scope of NCA enforceability heightens the likelihood that an employee will be asked to consider an NCA when joining a company, especially if state-level enforcement is stringent. Similarly, the restricted geographical applicability of NCA enforceability increases the likelihood that employees will contemplate NCAs when entering a company, particularly if state-level enforcement is widespread. The scope of enforcement should align with that of the private market, mirroring the enforceability found in public companies within the restricted geographical applicability.

To establish a causal relationship between outside opportunities and VC staged financing and to investigate the impact of changes in NCA grants on the level of outside opportunities for entrepreneurs and their subsequent influence on VC staged financing, a staggered difference-in-differences analysis is conducted around state-level variations in non-compete enforceability. I construct treatment groups based on the geographic locations of entrepreneurial firms, specifically whether they are located in states with high state-level enforceability scores, where the score exceeds 5 on the scale that ranges from 0 (weakest enforcement) to 12 (strictest enforcement). Additionally, these states exhibit NCA enforceability coverage above 40% based on reported percentages of firm-years with NCAs, following the state-level noncompete enforceability index composed by Kini et al., 2020, who constructed the index following the methodology proposed by Garmaise, 2011. Table 9 list all Garmaise state-level noncompete enforeability index with enforceable score and NCA coverage from 1992 to 2014.

The staggered diff-in-diff analysis centers on the treatment groups after the grants of NCAs. In terms of empirical analysis, I focus on the interaction term between the after NCAs grant period and state-level regulations, with the aim of capturing exogenous variation on the change of the number of financing rounds of entrepreneurial firms. The research design places emphasis on the limitations imposed on external opportunities by NCA enforcement, particularly within states characterized by high enforceability scores and extensive coverage. If the hold-up hypothesis suggests a causal effect on VC investment, the enforcement of NCAs is anticipated to restrict outside opportunities, subsequently reducing agency costs, diminishing bargaining power possessed by entrepreneurs, and lowering the need for multiple financing rounds raised by VCs. Consequently, it is expected that an exogenous increase in state-level NCA enforceability will lead to a reduction in the number of financing rounds facilitated by VCs, as greater enforceability is likely to lower external opportunities. This, in turn, results in fewer financing rounds.

5.2.3 Validity of Identification Strategy

The use of Two-Way Fixed Effects (TWFE) in Difference-in-Differences (DiD) regression can lead to biases in the estimation of treatment effects. This is because TWFE down-weights some of the earlier- vs. later-treated comparisons and up-weights some of the later- vs. earlier-treated comparisons, thereby increasing the influence of the potentially problematic 2 $\times$ 2s. Additionally, biases associated with TWFE event-study estimates could lead researchers to infer a lack of pre-trends when the parallel-trends assumption does not hold. These biases can result in Type-I and Type-II errors, where true treatment effects are either incorrectly estimated as significant or insignificant.

To mitigate the concerns of the potential bias in the standard Diff in Diff design of unable to capture the treatment effect heterogeneity.I adopted both ETWFE method and Callaway and Sant'Anna method to do the staggered diff in diff analysis. ETWFE is the extended TWFE, and the ETWFE estimator is an extension of the basic TWFE estimator that allows covariates to enter flexibly. By including covariates in the estimation, the ETWFE estimator can control for differences in treatment effects across different groups, which could capture the heterogeneity in the treatment groups, overall it can help to reduce the bias that arises from the basic TWFE estimator.

On the other hand, The DDD estimator (Callaway and Sant'Anna estimator) modifies the set of effective comparison units in the treatment effect estimation process by using a triple-difference approach. Specifically, it compares the difference in outcomes between treated and control groups before and after treatment, and then takes the difference of these differences across two different treatment groups. This approach ensures that the treatment group is not compared to itself in the estimation process, which can help to mitigate the biases that can occur with TWFE. Baker et al., 2022 shows that the DDD estimator can help to recover the actual treatment effects, reinforced it validity.

To validate the effectiveness of the staggered diff in diff strategy, I propose the following estimation strategy.

The prevalent use of staggered difference-in-differences (DiD) models has historically been viewed as robust in econometric analysis to address causal effects. Nevertheless, recent studies (Borusyak and Jaravel, 2018; Athey and Imbens, 2018; Callaway and Sant'Anna, 2021) have raised doubts about the validity of standard DiD regression estimates, particularly in scenarios involving staggered treatment timing, even when treatments are assigned randomly. Baker et al. (2022) further argue that while standard staggered DiD analysis is generally unbiased, combining staggered treatment timing with treatment effect heterogeneity can introduce bias. Notably, the interplay between staggered treatment timing and dynamic treatment effects magnifies the incorrect comparison issue inherent in standard staggered DiD analysis, specifically the DiD static effect estimates using Two-Way Fixed Effects (TWFE), which may yield wrong results in estimations.

Specifically, the use of Two-Way Fixed Effects (TWFE) in Difference-in-Differences (DiD) regression can lead to biases in the estimation of treatment effects. This is because TWFE down-weights some of the earlier- vs. later-treated comparisons and up-weights the other way around, thereby increasing the bias of the estimates. Additionally, biases associated with TWFE event-study estimates could lead researchers to infer a lack of pre-trends when the parallel-trends assumption does not hold. These biases can result in Type-I and Type-II errors, where true treatment effects are either incorrectly estimated as significant or insignificant.

To address concerns of potential bias in the standard DiD design when unable to capture treatment effect heterogeneity, I adopted two alternative staggered DiD estimators to estimate the average treatment effect of NCAs grants across states, including both the Extended Two-Way Fixed Effects (ETWFE) estimators and the Callaway and Sant'Anna triple-difference (DDD) estimator for the staggered DiD analysis. ETWFE extends the basic TWFE estimator by allowing flexible inclusion of covariates. This extension permits the ETWFE estimator to control for variations in treatment effects across different groups, which can account for heterogeneity in the treatment groups and reduce bias compared to the basic TWFE estimator.

Conversely, the DDD estimator (Callaway and Sant'Anna estimator) revises the set of effective comparison units during treatment effect estimation by employing a triple-difference approach. Specifically, it assesses outcome differences between treated and control groups before and after treatment, then contrasts these differences across two distinct treatment groups. This approach ensures that the treatment group is not compared to itself during estimation, thus helping mitigate potential biases associated with TWFE. Baker et al. (2022) have demonstrated that the DDD estimator effectively recovers actual treatment effects, further reinforcing its validity.

To validate the efficacy of the staggered DiD strategy, I propose the following estimation approach.

5.2.4 Estimation Strategy

The general set up of the staggered DID model adopted in my analysis shows in equation (5)

$$\left\{(Y_{i,1}, Y_{i,2}, \ldots, Y_{i,T}, D_{i,1}, D_{i,2}, \ldots, D_{i,T}, X_i)\right\}_{i=1}^{n} \tag{5}$$

$D_{i,t}$ is a dummy variable that takes a value of 1 if entrepreneurial firm i is treated in period t, i.e., after the state granted NCAs, and 0 otherwise. Additionally, a cohort dummy variable, denoted as $G_{i,g}$, takes a value of 1 if entrepreneurial firm i is initially treated at time g. This corresponds to the first year when the state's NCA enforceability score exceeds 4 and NCA coverage surpasses 40%, with a value of 0 otherwise. Furthermore, a comparison group labeled "never-treated" is represented as C, taking a value of 1 for entrepreneurial firms located in states where the NCA enforceability score falls below 5, or NCA coverage is less than 40%. To estimate the cohort-time-specific treatment effects while controlling for relevant covariates, the following regression equation is adopted:

$$Y_{it} = \alpha_1^{g,t} + \alpha_2^{g,t} * \|\{G_{i,g} = 1\} + \alpha_3^{g,t} * \|\{t > g\} + \beta_{g,t} * (\|\{G_{i,g} = 1\} * \|\{t > g\}) \tag{6}$$

These estimators allow for both not-yet-treated or never-treated as clean controls and demonstrate that $\beta_{g,t}$ is a valid estimator for $ATT_{g,t}$ under the assumptions of no anticipation and unconditional parallel trends. They also accommodate heterogeneity without biasing the estimates. Specifically, the average treatment effect for entrepreneurial firms first treated at time period g, in calendar time t, is given by:

$$ATT(g,t) = E[Y_t(g) - Y_t(0) \,|\, G_g = 1], \quad \text{for } t \neq g. \tag{7}$$

Following the contract literature mentioned above, in my sample, I have states where the NCA enforceability is below 5 or NCA coverage is below 40% throughout the sample period. Therefore, I have the clean control group represented as $C = 1$. Consequently, I have adopted both the "never treated" group (as shown in Equation (8)) and the "not-yet-treated" group (as shown in Equation (9)) as my control groups. The regression estimation is provided below:

$$E[Y_t(0) - Y_{t-1}(0) \,|\, X, G_g = 1] = E[Y_t(0) - Y_{t-1}(0) \,|\, X, C = 1] \tag{8}$$

For each $t \in \{2, \ldots, T\}$ and $g \in G$ such that $t \neq g$.

$$E[Y_t(0) - Y_{t-1}(0) \,|\, X, G_g = 1] = E[Y_t(0) - Y_{t-1}(0) \,|\, X, D_s = 0, G_g = 0] \tag{9}$$

For each $(s,t) \in \{(s,t) \in \{2,\ldots,T\} \times \{2,\ldots,T\} \mid g \in G, \text{ such that } t \neq g, s \leq t\}$

In accordance with the staggered DID regression estimator outlined previously, I constructed event cohorts, each comprising a treated state that granted NCAs with an enforceability score above 4 and NCA coverage above 40% during a specific year, following the Garmaise state-level noncompete enforcement index as depicted in Table 9. I employed all other state-years that did not experience such legal reforms as a control group for the 'not-yet-treated' DID analysis, while another control group consisted of state-years that never underwent such legal reforms for the 'never-treated' DID analysis. The treatment group was defined as entrepreneurial firms located in the treated state within each event cohort, marked as 1 and 0 otherwise, with the 'post' variable set as 1 in the period following the NCA law grant and 0 otherwise. To mitigate potential biases, no control variables were incorporated. The results pertaining to the average treatment effect for the treatment group (the interaction term) are presented in Table 10. Panel A displays results applying the Extended TWFE method, while Panel B presents estimates using the Callaway and Sant'Anna method. The table reveals that the average treatment effect for the treatment group is negative and statistically significant. This suggests a decrease in financing rounds for entrepreneurial firms located in treated states following the enforcement of NCAs, attributed to the decreased outside opportunities faced by entrepreneurs. These findings support the hypothesis that the enforcement of NCAs mitigates hold-up problems for VC investors, leading to lower demand for financing rounds compared to the control group. To capture the dynamic changes in the average treatment effect for the treated group in each year following the enforcement of NCAs, Figure 3 illustrates the after-treatment effect on treated entrepreneurial firms using the ETWFE estimation method with 'not-yet-treated' as control groups while Figure 4 shows the before-and-after treatment effect on treated entrepreneurial firms using the Callaway and Sant'Anna estimation method with 'not-yet-treated' as control groups. Figures employing 'never treated' as control groups are provided in the online appendix. Both figures depict a decreasing trend in the average number of financing rounds required for firms located in states where NCAs are enforced, consistent with the hypothesis regarding the hold-up phenomenon.

The results unequivocally reveal substantial disparities between the treatment group (subject to enforced NCAs) and the control group (without enforced NCAs), thereby affirming the efficacy of the identification strategy. In summary, the DID estimation unequivocally substantiates the presence of a causal relationship between the level of outside opportunities faced by entrepreneurs and the number of financing rounds raised by venture capitalists.

5.3 IV-Approach Identification Strategy

As noted earlier, the positive correlation between the number of financing rounds and entrepreneurs' outside opportunities of VCs might be influenced by potentially omitted variables that are directly linked to the characteristics of VC investors, entrepreneurs, or entrepreneurial firms. Additionally, there might exist the possibility of reverse causality from entrepreneurs' external opportunities to social connectedness. Complementing the natural experiment diff-in-diff approach discussed above, this section employs an instrumental variable (IV) strategy to address the potential endogeneity concerns. This strategy aims to control for endogeneity in the geographic structure of social networks using two-stage least squares (2SLS) regressions. Specifically, three additional IVs are employed to instrument the social connectedness measure.

Following the study of Donaldson and Hornbeck (2016), I initially use county-to-county transportation costs dating back to 1920 ($cost_{1920}$) as the first instrumental variable. These historical travel costs are derived from a combination of railways, canals, and cattle paths from 1920, reflecting the cheapest means of travel between counties. Given the limited expansion of the U.S. railroad networks after the 1920s, the lowest travel cost in 1920 is considered a proxy for travel costs over the past two decades. However, transportation costs are influenced by diverse factors, including technological advancements, changes in infrastructure, and market dynamics, which can substantially vary over time. Consequently, using transportation costs from 1920 cannot be assumed equivalent to current costs without rigorous analysis and adjustments accounting for these changes. To address this, I introduce a second instrumental variable ($cost_{noRR}$), which offers an alternative measure of transportation cost. This measure remains constant over time as it disregards the railroad network among counties, providing a more reliable estimate of current transportation costs.

Furthermore, the validity of using transportation costs as an instrumental variable for the geographic structure of social networks is supported for several reasons. First, as established by Donaldson and Hornbeck (2016), transportation costs accurately measure market access, referring to a location's connectivity to markets for goods and services. Such costs reflect the expenses associated with moving goods between locations, with lower transportation costs indicative of greater market access and connectivity to goods and services. Notably, transportation costs are influenced not solely by physical distance but are also determined or significantly influenced by the cost of transportation, encompassing both temporal and financial aspects of moving goods. This nuanced relationship potentially correlates with the geographic structure of social networks, as transportation costs impact travel ease and frequency between locations. For example, higher transportation costs between two areas might discourage travel, leading to weaker social ties between them. Conversely, lower transportation costs encourage travel and may foster stronger social connections, highlighting a substantial correlation between the geographic structure of social networks and transportation costs.

In contrast, transportation costs exhibit no discernible association with the outside opportunities faced by entrepreneurs. Should the rationale for instrumental variable construction align with expectations, transportation costs could serve as a valid instrumental variable in the analysis.

To save space, the results of the first-stage regression are provided in the online appendix. As anticipated, the negative correlation between the social connectedness index and transportation cost aligns with expectations, as transportation costs are influenced by factors beyond physical distance. Specifically, a 10% increase in the geographic social network corresponds to a decrease of 0.1017 units in transportation cost when using the 1920 historical data, and a decrease of 0.073 units when considering transportation cost without railroad. To evaluate the hold-up hypothesis, I follow the approach used in equations (3) and (5) to construct instrumental variables for both passive and proactive outside opportunities faced by entrepreneurs.

While the first-stage regression indicates the relevance of transportation costs, potential bias in estimates due to weak instruments remains a concern. The reported F-statistics for the joint significance test of the proposed instruments are notably large. Additionally, the Stock and Yogo (2005) weak instrument test yields statistics surpassing the critical value, affirming the validity of transportation costs, both $cost_{1920}$ and $cost_{noRR}$, as instrumental variables.

The results of the second-stage regression are displayed in Table 11, featuring the number of VC financing rounds as the dependent variable and the predicted values of passive outside opportunities faced by entrepreneurs as the independent variables. Across all columns, the coefficient estimates of the social connectedness index are consistently positive for both instrumental variables.

Comparison between the findings of the baseline regression and the 2SLS regression unveils a compelling observation: the magnitudes of the 2SLS coefficient estimates are significantly larger than those in the baseline regression. Specifically, utilizing the 1920 transportation cost data results in an 8.3 times increase in magnitude, while utilizing transportation cost without railroad leads to a 112 times increase. This outcome implies that baseline regressions introduce downward bias in coefficient estimates due to endogeneity concerns. Furthermore, this observation implies that omitted variables concurrently augment the desirability of VC staging when outside opportunities are substantial.

In an untabulated analysis, I extend the 2SLS regression framework to control for endogeneity issues regarding the monitoring hypothesis. However, the results continue to deviate from the anticipated theoretical predictions.

5.3.1 Alternative instruments approaches

Building on the approach of Ackerberg and Botticini (2002), I adopt an alternative technique to address the endogeneity challenge. Specifically, I utilize market factors as instrumental variables. These market factors are creased by incorporating all pertinent fixed effects related to each specific firm-market interaction. In my dataset, I encompass 52 industries, 1083 counties, and the associated 859 interaction terms of industry and state, in total of 1994 dummy variables to construct the market factors. This comprehensive set of variables serves as instruments for the outside opportunities faced by entrepreneurs. The detailed results of this analysis are presented in the online appendix. Across all columns and fixed effects, the coefficient estimates for the outside opportunities faced by entrepreneurs remain positive and statistically significant. This robust pattern lends support to the hold-up hypothesis's implications, reinforcing the notion that the presence of outside opportunities indeed influences VC staging behaviors.

6 Entrepreneurial Firms Outcome of VC staged Financing

The subsequent section examines the post-investment performance of entrepreneurial firms, specifically focusing on how VC staged financing influences their ultimate success, such as going public or achieving successful acquisition.

Conflicting empirical findings and hypotheses have emerged in previous literature. Gompers (1995) suggests a positive correlation between the number of capital infusions and the post-investment performance of entrepreneurial firms, as venture capitalists have the option to abandon firms if they do not perceive future prospects. Conversely, Ewens et al. (2016) argue for a negative correlation, attributing it to behavioral biases and opportunity costs throughout the funds' life cycle. According to their view, an increased number of financing rounds is more likely to lead to firm failure, decrease the likelihood of IPOs, and result in lower exit values. This study aims to reconcile these competing hypotheses and empirical results to precisely determine how VC staged financing impacts post-investment performance.

The above empirical analyses have provided substantiating evidence for the proposition that VC staged financing can be attributed to the hold-up hypothesis. This section will address the post-investment performance of entrepreneurial firms in relation to the hold-up hypothesis, specifically to discover the relationship between the number of capital infusions in VC investment and post-investment performance. The hold-up hypothesis predicts that with lower outside opportunities available to entrepreneurs, the agency costs between entrepreneurs and VC investors decrease, resulting in optimal post-investment performance due to reduced asymmetric information and investment uncertainty, i.e. lower conflict between entrepreneurs and VC investors. Two situations align with these predictions. Firstly, without conditioning on staged financing, a negative correlation between the severity of outside opportunities faced by entrepreneurs and the level of agency costs between VC investors and entrepreneurs is expected to be observed if the hold-up hypothesis holds. Secondly, in more common scenarios, where entrepreneurs encounter relatively high outside opportunities, increased rounds of financing with shorter durations can mitigate the hold-up problem, lower agency costs, and enhance subsequent performance. In other words, the number of capital infusions can improve post-investment entrepreneurial firm performance only when the entrepreneur's hold-up problem is severe, indicating high outside opportunities.

Existing literature (Gompers and Lerner, 2000; Brander et al., 2002; Nahata, 2008) has already established that both initial public offerings (IPOs) and acquisitions are considered successful exits, generating the highest returns for both entrepreneurs and VC investors. For instance, Gompers (1995) demonstrates that entrepreneurial firms going public yield the highest average return for venture capitalists. Sahlman (1990) asserts that almost all returns for VC investors are earned through portfolio companies that eventually go public. Therefore, the success measure for entrepreneurial firms in this study is based on whether they go public or achieve successful acquisition. A success exit dummy variable is created, taking a value of 1 if the firm goes public or is acquired, and 0 otherwise.

Table 12 presents the logit regression results for the effect of staged financing on entrepreneurial firm post-investment performance. The dependent variable is the dummy variable indicating the outcome results of the entrepreneurial firm. The predictions of the hold-up hypothesis are tested in this table. The main explanatory variable is the number of financing rounds received by entrepreneurial firms, passive outside opportunities faced by entrepreneurs (industry average SCI), and the interaction term between passive outside opportunities and the number of financing rounds. If the first situation (mentioned above) of the hold-up hypothesis is supported, the coefficient estimates of passive outside opportunities (represented by industry average SCI) are expected to be negative. Conversely, if the second situation is supported, the coefficient estimates of the interaction term are expected to be positive and statistically significant. However, as shown in the table, neither the coefficient estimates of the industry average SCI nor the number of financing rounds are consistent with the predictions or statistically significant. The results demonstrate mixed relationships between subsequent firm performance and the number of financing rounds. They partially align with the findings reported by Ewens et al. (2016). For example, in columns 2, 3, and 4, with different control and fixed effects, the coefficient estimates on the number of financing rounds are negative, statistically significant, and economically meaningful, indicating a negative correlation with post-investment performance. Conversely, columns 7 and 8 partially support the results found by Gompers (1995), displaying positive correlations. To reconcile the inconsistent results across different controls and fixed effects, the interaction term of SCI and the number of financing rounds, which represents a conditional situation, is introduced. If the second situation of the hold-up hypothesis is supported, the coefficient estimates on the interaction term are expected to be positive and statistically significant since increased financing rounds can reduce agency costs and improve subsequent performance when faced with a high hold-up problem. The coefficient estimates of the interaction term, as shown in Table 12, are positive and significant at the 5% level. This evidence suggests that VC staging increases the firm's likelihood of achieving success when entrepreneurs face high passive outside opportunities. To be more concrete, for example, the coefficient estimates reported in column 1 suggest that if the interaction term increases by 1 unit, the probability of a successful exit for entrepreneurial firms increase by 1.02%. To account for unobserved time-variant fixed effects, VC investor effects, and entrepreneurial firm effects, additional tests are conducted, and the results are reported in the online appendix.

To test proactive outside opportunities, the main explanatory variables are replaced with associated average SCI. The results, shown in Table 13, are similar to those reported in Table 12, with the coefficient estimates of the interaction term with proactive outside opportunities being positive, statistically significant, and economically meaningful. Additional tests are provided in the online appendix to save space.

Overall, the results align more closely with Gompers' (1995) findings, suggesting a positive correlation between the number of financing rounds and post-investment performance, conditional on entrepreneurs facing high outside opportunities.

6.0.1 Robustness Test using Inside Rounds

Ewens et al. (2016) underscore the importance of inside investors who, by virtue of their prior investments, possess superior information and valuable insights into addressing hold-up problems. To further examine whether the increased number of financing rounds can alleviate agency costs stemming from entrepreneurs' outside opportunities (hold-up costs), a focus on inside VC investors becomes particularly pertinent. These investors are particularly relevant to the hold-up theory due to their possession of more private information compared to their counterparts. This section investigates whether the hold-up issue contributes to agency concerns and whether staged investment behavior serves as a viable solution.

In pursuit of these objectives, an analysis is conducted specifically on the effect of staging on the performance of entrepreneurial firms, considering only inside VC investors. Table 14 presents the results of a logit regression aimed at assessing this relationship. The main explanatory variables include the number of inside financing rounds involving VC investors who had previously invested in the firm, the passive outside opportunities faced by entrepreneurs, and the interaction term between passive outside opportunities and the number of inside financing rounds. The outcomes of this analysis complement the primary hold-up hypothesis performance test, as demonstrated in Table 12, and again partially align with empirical findings by Gompers (1995) and Ewens et al. (2016). However, neither the outside opportunities faced by entrepreneurs nor the number of financing rounds significantly impact the post-investment performance of entrepreneurial firms. Consequently, conclusive conclusions regarding the influence of staged financing on post-investment performance or the impact of entrepreneurial hold-up costs on such performance cannot be drawn, given the inconsistent and statistically unstable coefficient estimates across diverse control and fixed effects.

To address this inconsistency, the interaction term of outside opportunities and the number of inside financing rounds, denoting a conditional scenario, is introduced. Consistent with the findings presented in Table 12, the coefficient estimates for this interaction term are consistently positive and statistically significant across various controls and fixed effects. This outcome validates the hold-up hypothesis. Specifically, an increase in inside financing rounds corresponds to a reduction in agency costs and an improvement in subsequent performance, particularly in cases where hold-up problems are pronounced for entrepreneurs. Notably, inside VC investors, owing to their possession of superior private information and insights into entrepreneurial intentions, are better equipped to gauge the severity of hold-up problems and devise effective strategies to mitigate agency costs, thus enhancing post-investment performance. This assertion is substantiated by the coefficient estimate of 0.304 for the interaction term in column 1, which is 1.7 times larger than the results reported in Table 12. Economically, a 1-unit increase in the interaction term correlates with a 1.04% rise in the probability of successful exit for entrepreneurial firms. In summary, these findings robustly support the hold-up hypothesis and empirically reconcile the relationship between staged financing and post-investment performance. Supplementary analyses, considering unobserved time-variant fixed effects, VC investor effects, and entrepreneurial firm effects, are conducted, and their outcomes are detailed in the online appendix.

To summarize, the findings presented herein indicate that the influence of VC staging on post-investment performance of entrepreneurial firms is contingent upon the outside opportunities available to the entrepreneurs. The results align more closely with the assertions made by Gompers (1995), suggesting a positive correlation between the number of financing rounds and subsequent performance. Additionally, the results support the implications of the hold-up hypothesis.

7 Conclusion

This study investigates the motivations underpinning the utilization of staged VC financing. It employs novel proxies derived from geographical structures of social connections, which serve as an effective indicator of weak ties, to gauge the potential external opportunities confronting entrepreneurs. Empirical assessments are conducted to scrutinize the well-established theoretical proposition, known as the hold-up hypothesis, positing that staged financing can mitigate managerial hold-up concerns. The analysis affirms the role of the hold-up problem as a motivating factor behind the utilization of staged VC financing for entrepreneurs.

Specifically, the findings demonstrate that in the U.S. VC market, higher outside opportunities faced by entrepreneurs are associated with increased hold-up problems between VC investors and entrepreneurs, leading to a more credible threat of entrepreneurial firm failure. To mitigate this hold-up problem, VC investors tend to employ a greater number of financing rounds with shorter durations and smaller amounts per round. This gradual transformation of entrepreneurs' human capital into the firm's physical assets helps reduce the hold-up problem.

Furthermore, the study reveals a positive correlation between the post-investment performance of entrepreneurial firms and the number of financing rounds when the hold-up problem is more severe. Specifically, in cases where entrepreneurs face substantial potential outside opportunities, a higher number of financing rounds increases the likelihood of a successful exit for the entrepreneurial firm. These findings are robust to various model specifications, inclusion of fixed effects and application of econometric approaches to address endogeneity concerns. Overall, the evidence supports the hold-up hypothesis.

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Figures

Figure 1: The Amount of Investment in U.S. Private Market Across Years.

The figure presented below illustrates the trends in venture capital, private equity, and private debt investments in the United States private market from 1990 to 2019. It provides information on the number of entrepreneurial firms receiving private investment over the years, as depicted by the labeled bar. Additionally, the line represents the corresponding amount of investment in million dollars made in the private market during this period. The data utilized for this analysis were sourced from the Preqin database, which specializes in VC/PE investment information.

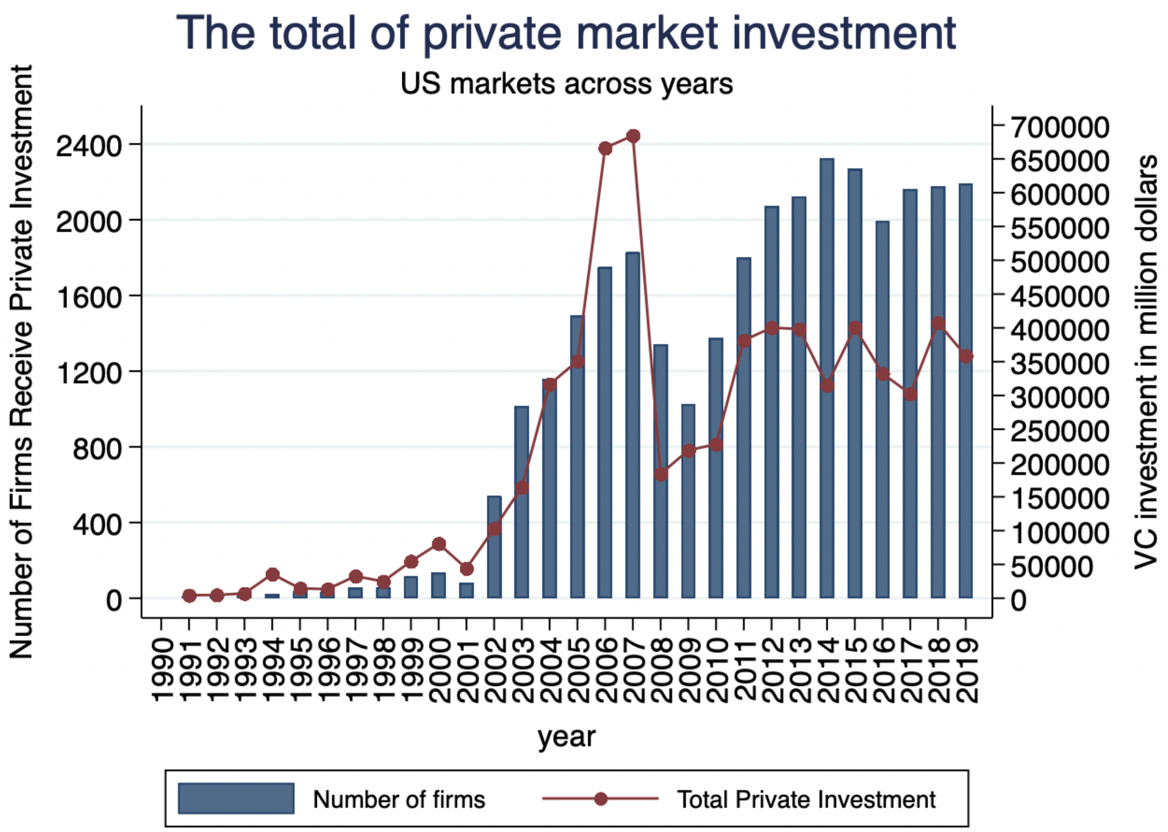


Figure 2: Heat Map of the Social Connections of each County in the United States to Santa Clara County.

The following figure depicts a heat map illustrating the social connectedness between Santa Clara County, CA, the location of Silicon Valley, and other counties in terms of venture capital and private equity (VC/PE) investments. The map represents the level of social connections based on the intensity of the color. Darker colors indicate a higher degree of social connections between a specific county and Santa Clara County, CA. It is important to note that a blank space on the map does not imply the absence of social connections; rather, it indicates that no VC/PE investments were made between those counties within the specified time period. The map excludes Hawaii and Alaska states, as well as islands with longitudes above 0 or below -130.

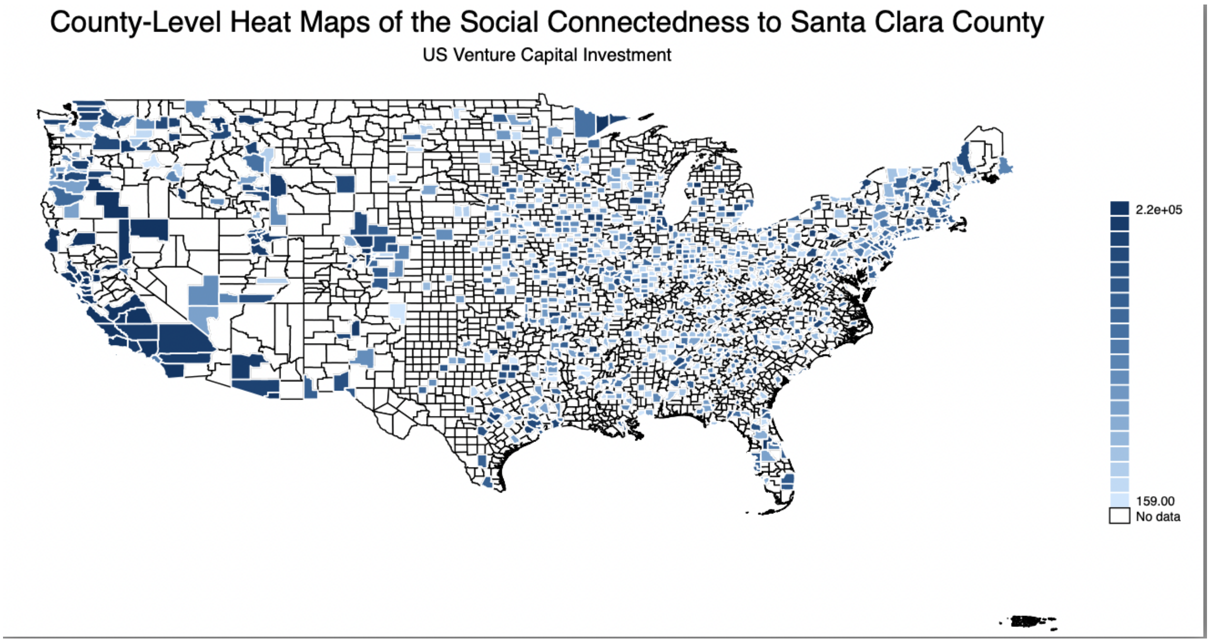


Figure 3: Dynamic Treatment Effects Using ETWFE.

The figure presented below illustrates the dynamic evolution of the average treatment effect on the treatment groups employing ETWFE event-study estimates. It encompasses relative-time periods from l = g to l = g + 30 surrounding the enforcement of NCAs (l = g + 0). The treatment group comprises entrepreneurial firms situated within the treated state for each event cohort, characterized by a NCA enforceability score exceeding 4 and a coverage ratio surpassing 40%. Conversely, the control groups encompass all other firms located in state-years that did not undergo such legal reforms. The blue line represents the average treatment effect before the enforcement of NCAs, while the red line depicts the average treatment effect after the enforcement of NCAs.

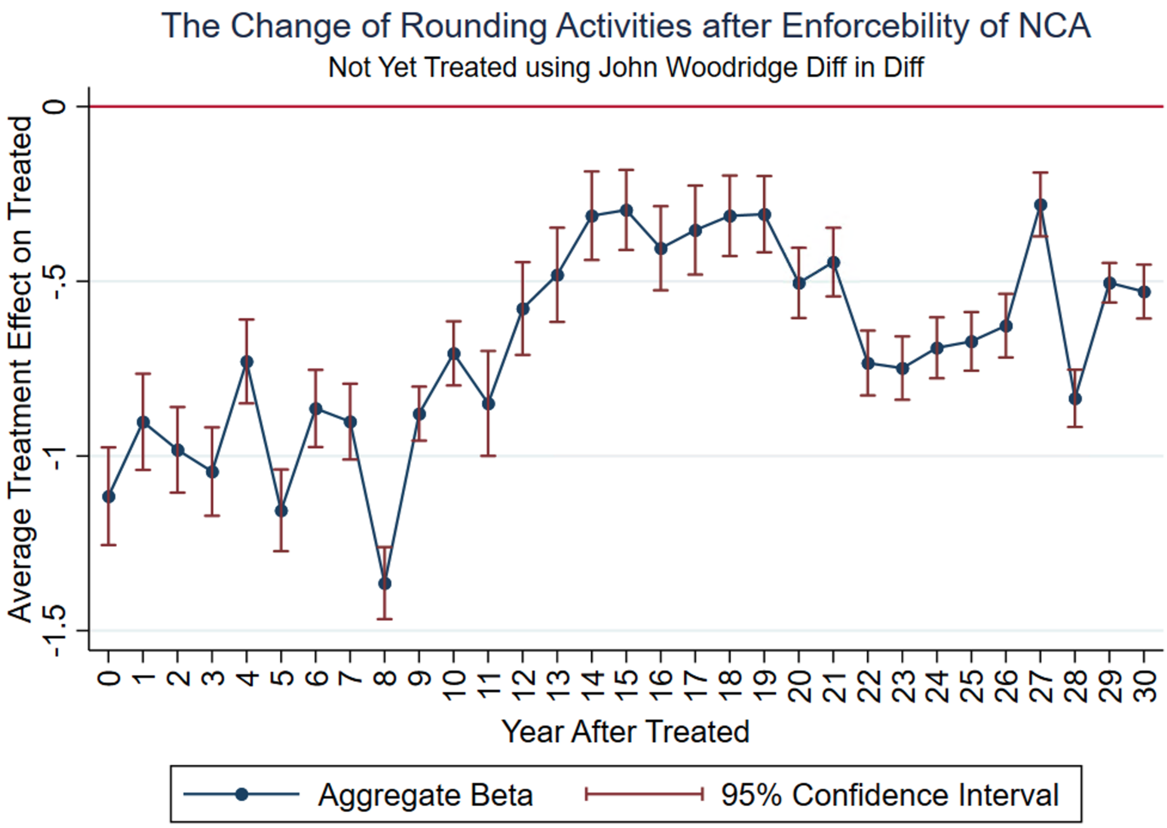
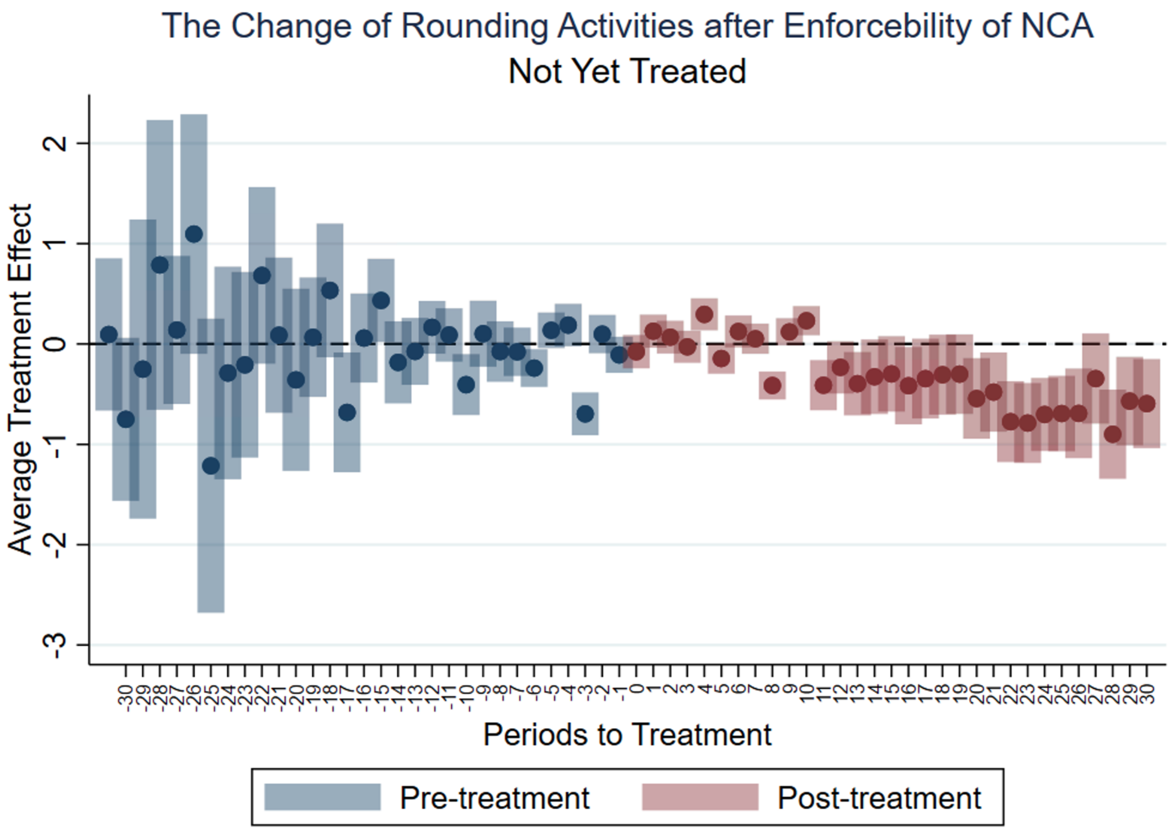


Figure 4: Dynamic Treatment Effects Using Callaway and Sant'Anna Estimators.

The figure presented below illustrates the dynamic evolution of the average treatment effect on the treatment groups employing Callaway and Sant'Anna event-study estimates. It encompasses relative-time periods from l = g to l = g + 30 surrounding the enforcement of NCAs (l = g + 0). The treatment group comprises entrepreneurial firms situated within the treated state for each event cohort, characterized by a NCA enforceability score exceeding 4 and a coverage ratio surpassing 40%. Conversely, the control groups encompass all other firms located in state-years that did not undergo such legal reforms. The blue line represents the average treatment effect on the treated groups, while the red line depicts the corresponding 95% confidence intervals.



Tables

Table 1: Time Series of Private Market Investment in the United States

The table below provides information on the number of entrepreneurial firms that received venture capital/private equity (VC/PE) financing in the United States from 1995 to 2021. It includes data on the average number of financing rounds per entrepreneurial firm each year, the total number of rounds received based on the number of entrepreneurial firms, the average amount of investment received from VC/PE investors, and the total amount invested by VC/PE investors. The investment amounts listed are in millions of dollars.

Year	Average Rounds of Venture Capital Financing	Rounds of Venture Capital Financing	Average Amount of Venture Capital Investment (Million Dollars)	Amount of Venture Capital Invest-ment(Million Dollars)	Number of Entrepreneurs
1995	2.054	76	395.276	14625.21	37
1996	1.765	60	396.048	13465.62	34
1997	1.963	106	607.042	32780.27	54
1998	2.052	119	429.256	24896.87	58
1999	1.888	219	470.071	54528.21	116
2000	1.806	242	603.104	80815.88	134
2001	2.013	161	551.534	44122.72	80
2002	3.189	1725	190.590	103108.9	541
2003	3.196	3241	162.103	164372	1014
2004	3.173	3674	273.235	316406.5	1158
2005	2.993	4465	235.223	350952	1492
2006	2.820	4930	381.116	666190.8	1748
2007	2.813	5140	374.733	684636.2	1827
2008	2.972	3986	137.096	183845	1341
2009	3.041	3120	213.345	218891.5	1026
2010	2.985	4102	165.895	227939.4	1374
2011	2.932	5275	212.058	381491.4	1799
2012	2.735	5664	193.283	400288.9	2071
2013	2.743	5820	187.700	398299.5	2122
2014	2.728	6341	135.652	315256.3	2324
2015	2.779	6301	176.765	400725.3	2267
2016	2.693	5368	166.833	332497.9	1993
2017	2.455	5305	139.916	302359.2	2161
2018	2.353	5121	187.353	407681	2176
2019	2.226	4876	163.765	358645.6	2190
2020	1.923	4132	107.535	231093.6	2149
2021	1.490	4612	157.606	487791.2	3095

Table 2: Time Series of Outcomes for VC/PE Backed Entrepreneurial Firms in the United States

The table below presents the outcome summaries of entrepreneurial firms that received venture capital/private equity (VC/PE) financing in the United States from 1995 to 2021. It includes the number of firms that underwent an initial public offering (IPO), were acquired or merged, went into liquidation, or remained private. The second column indicates the number of entrepreneurial firms for each year. Columns 3, 4, and 5 display the count of firms that went public, were acquired or merged, or went into liquidation or remained private, respectively. Columns 6, 7, and 8 represent the corresponding percentages.

Year	Number of Entrepreneurs	IPO	Acquisition	Liquidation/Remain Private	IPO(%)	Acquisition(%)	Liquidation/Remain Private(%)
1995	83	13	14	56	15.66%	16.87%	67.47%
1996	110	17	15	78	15.45%	13.64%	70.91%
1997	120	17	10	93	14.17%	8.33%	77.50%
1998	159	13	16	130	8.18%	10.06%	81.76%
1999	191	20	27	144	10.47%	14.14%	75.39%
2000	222	15	32	175	6.76%	14.41%	78.83%
2001	155	10	22	123	6.45%	14.19%	79.35%
2002	289	21	62	206	7.27%	21.45%	71.28%
2003	498	30	121	347	6.02%	24.30%	69.68%
2004	703	49	151	503	6.97%	21.48%	71.55%
2005	930	38	209	683	4.09%	22.47%	73.44%
2006	1108	44	233	831	3.97%	21.03%	75.00%
2007	1313	53	278	982	4.04%	21.17%	74.79%
2008	1070	42	214	814	3.93%	20.00%	76.07%
2009	856	35	193	628	4.09%	22.55%	73.36%
2010	1117	49	235	833	4.39%	21.04%	74.57%
2011	1175	53	258	864	4.51%	21.96%	73.53%
2012	1367	63	243	1061	4.61%	17.78%	77.62%
2013	1205	62	271	872	5.15%	22.49%	72.37%
2014	1203	75	289	839	6.23%	24.02%	69.74%
2015	1245	59	325	861	4.74%	26.10%	69.16%
2016	1104	68	277	759	6.16%	25.09%	68.75%
2017	1128	67	287	774	5.94%	25.44%	68.62%
2018	1000	63	308	629	6.30%	30.80%	62.90%
2019	774	65	267	442	8.40%	34.50%	57.11%
2020	682	121	248	313	17.74%	36.36%	45.89%
2021	529	54	292	183	10.21%	55.20%	34.59%

Table 3: Time Series of Average Round for each Outcome for VC backed Firms in the United States

The table below presents the average number of financing rounds for different outcomes of entrepreneurial firms that received financing from venture capital/private equity (VC/PE) from 1995 to 2021. The second column represents the average number of rounds received for firms that ended up in an initial public offering (IPO). The third column shows the average number of rounds received for firms that were merged or acquired. The last column displays the average number of rounds received for firms that went into liquidation or remained private at the time of calculation.

Year	Average Rounds of Firms Went IPO	Average Rounds of Firms Went Merger	Average Rounds of Firms Went Liquidate/Private
1995	1.231	1.286	1.107
1996	1.235	1.067	1.244
1997	1.294	1.200	1.215
1998	1.308	1.375	1.277
1999	1.150	1.333	1.340
2000	1.800	1.438	1.360
2001	1.600	1.455	1.447
2002	1.381	1.339	1.403
2003	1.733	1.529	1.403
2004	1.816	1.589	1.525
2005	2.053	1.856	1.621
2006	2.568	2.009	1.704
2007	2.075	2.183	1.871
2008	3.190	2.332	2.128
2009	3.914	2.648	2.255
2010	3.837	2.494	2.252
2011	3.415	2.690	2.242
2012	5.000	2.996	2.356
2013	4.355	2.974	2.492
2014	4.613	3.304	2.603
2015	4.610	3.068	2.738
2016	4.294	2.939	2.810
2017	4.224	3.118	2.801
2018	4.825	3.328	3.037
2019	4.385	3.494	3.260
2020	4.909	3.613	3.498
2021	4.333	3.562	4.120

Table 4: Summary Statistics

The table below presents comprehensive summary statistics for the variables employed in this study, encompassing social connectedness measurement, distance variables, industry-level variables, and venture capital (VC) characteristic variables. Specifically, the social connectedness measurement (SCI) quantifies the number of Facebook links between the headquarters' counties of entrepreneurial firms and VC/PE firms, adjusted by the product of the populations in these counties (multiplied by 10^{12}). For deals within the United States, the monitoring cost, computed using the county-level SCI, is defined as the natural logarithm of the SCI variable. Distance represents the geographical distance in miles between the headquarters county of an entrepreneurial firm and that of a VC/PE firm. Passive outside opportunities are determined by calculating the average SCI between the headquarter locations of entrepreneurs and firms within the same industry. Proactive outside opportunities, on the other hand, are determined by averaging the SCI between the local headquarter location of an entrepreneur and the SCI between the headquarter locations of entrepreneurs and VC investors. The logarithm of county-level distance is defined as the natural logarithm of (1 + distance). A similar logarithmic transformation is applied to the log of industry average distance. Additionally, industrial level variables are derived from Compustats SIC code, while VC characteristics are calculated based on the Preqin dataset.

Variable	**Count**	**Mean**	**S.D.**	**Minimum**	**Maximum**
Entrepreneur's Outside Opportunities–Passively					
Outside Opportunities (Passively)	147207	10.115	1.534	7.791	13.946
Log of Industry Average Distance	147207	7.186	0.128	6.851	7.391
Entrepreneur's Outside Opportunities–Actively					
Outside Opportunities (Proactively)	118068	12.100	2.516	5.692	19.953
Log of Distance County Level	118068	4.817	2.796	0	8.531
Control Variable					
Number of Financing Rounds	117575	3.524	2.902	1	25
Round Duration	50514	18.378	13.901	0	209
Number of VC investors	117575	5.045	3.605	1	58
Log of Investment Amount at First Round	117575	1.171	1.596	-4.605	7.719
Industry Asset Tangibility	117575	0.172	0.131	0.001	0.920
Industry Market/Book Ratio	117575	0.508	21.351	-1208	800.819
Industry R&D/Asset	117575	0.183	0.343	0	34.868
Log of Investment Amount for VC investor	117575	6.991	2.349	-4.605	15.954
VC age	117575	18.587	10.969	0	62
Log of Total Deal Raised by Firm	117575	3.750	1.754	-4.605	10.840
First Age at First Round	117575	2.174	3.944	0	180

Table 5: Baseline regression for Hold-up hypothesis (Passive Outside Opportunity)

The table below presents the results of the baseline regression analysis investigating the hold-up hypothesis for VC investment in the United States. The primary independent variable is the outside opportunities (passively), which measured using average SCI among the headquarter location of the entrepreneurs and that of the firms in the same industry. The dependent variable is the number of financing rounds received by an entrepreneurial firm. The analysis includes control variables at the industry level, such as average industry asset tangibility, average industry market-to-book ratio, and average industry RD ratio. Additionally, the regression incorporates VC characteristics variables, including the VC's total investment amount, VC age, and success rate. Firm characteristics considered are the number of VCs invested in, the number of financing rounds received in the initial round, and the total funds raised by the firm. Data regarding entrepreneurial firms and VC/PE firms are sourced from the Preqin database, while industry average data are obtained from Compustat. Heteroskedasticity-robust standard errors are reported in parentheses. Statistical significance is denoted by *, **, and *** at the 10%, 5%, and 1% levels, respectively.

	Number of Financing Rounds					
	(1)	(2)	(3)	(4)	(5)	(6)
Outside Opportunity (Passively)	0.185	0.0462	0.0181	0.0190	0.0508	0.0317
	(66.47)***	(3.61)***	(4.09)***	(2.54)**	(2.30)**	(2.98)***
Geographic Distance	1.708	0.727	0.306	0.272	0.633	-0.0542
	(63.98)***	(6.08)***	(5.79)***	(2.99)***	(1.97)**	(-0.36)
Number of Syndicated VC		0.0731	0.0396	0.0199	0.0477	0.0134
		(4.43)***	(13.76)***	(5.87)***	(3.01)***	(3.57)***
Industry Asset Intangibility		-0.449	-0.342	-0.257	-3.063	-2.614
		(-1.99)*	(-5.65)***	(-2.99)***	(-2.54)**	(-8.53)***
Industry Market to Book Ratio		0.000349	0.000286	0.000218	-0.000494	-0.000316
		(1.48)	(1.01)	(0.75)	(-1.34)	(-1.12)
Industry R&D Ratio		-0.182	-0.181	-0.0932	0.168	0.121
		(-1.45)	(-3.40)***	(-2.04)**	(1.58)	(3.04)***
Geographic Distance Control	yes	yes	yes	yes	yes	yes
Venture Characteristic Control	no	yes	yes	yes	yes	yes
Entrepreneurial Firms Characteristic Control	no	yes	yes	yes	yes	yes
Entrepreneurial Firms Outcome Control	no	yes	yes	yes	yes	yes
Year fixed effect	no	yes	yes	no	no	no
County fixed effect	no	no	no	yes	no	no
VC firm fixed effect	no	no	yes	yes	no	no
VC firm * Industry fixed effect	no	no	no	no	no	yes
Industry fixed effect	no	no	no	no	yes	no
N	319719	184370	173650	173652	184370	184370
adj. R-sq	0.033	0.075	0.178	0.151	0.090	0.358

Table 6: Baseline regression for Hold-up hypothesis (Passive Outside Opportunity) with different specification

The table below presents the results of the baseline regression analysis investigating the hold-up hypothesis for VC investment in the United States. The primary independent variable is the outside opportunities (passively), which measured using average SCI among the headquarter location of the entrepreneurs and that of the firms in the same industry. The dependent variable is the amount investment at each round. The analysis includes control variables at the industry level, such as average industry asset tangibility, average industry market-to-book ratio, and average industry RD ratio. Additionally, the regression incorporates VC characteristics variables, including the VC's total investment amount, VC age, and success rate. Firm characteristics considered are the number of VCs invested in, the number of financing rounds received in the initial round, and the total funds raised by the firm. Data regarding entrepreneurial firms and VC/PE firms are sourced from the Preqin database, while industry average data are obtained from Compustat. Heteroskedasticity-robust standard errors are reported in parentheses. Statistical significance is denoted by *, **, and *** at the 10%, 5%, and 1% levels, respectively.

	Investment Amount at Each Round					
	(1)	(2)	(3)	(4)	(5)	(6)
Outside Opportunity (Passively)	-1.456	-0.374	-0.0303	-0.0523	-0.306	-0.0800
	(-35.05)***	(-6.37)***	(-0.96)	(-1.52)	(-7.24)***	(-2.05)**
Geographic Distance	-10.11	-2.390	-0.303	-0.827	-3.018	-0.269
	(-22.30)***	(-3.75)***	(-0.82)	(-1.97)**	(-2.15)**	(-0.43)
Number of Syndicated VC		0.612	0.691	0.807	0.460	0.506
		(6.74)***	(31.20)***	(28.32)***	(6.09)***	(21.32)***
Industry Asset Intangibility		3.769	2.134	3.640	3.255	12.52
		(3.63)***	(4.87)***	(7.54)***	(0.77)	(5.62)***
Industry Market to Book Ratio		0.00527	0.00122	0.00338	0.00700	0.0127
		(1.22)	(0.43)	(1.26)	(4.26)***	(1.99)**
Industry R&D Ratio		0.746	0.215	0.614	1.454	1.044
		(1.42)	(1.06)	(2.59)***	(1.21)	(2.87)***
Geographic Distance Control	yes	yes	yes	yes	yes	yes
Venture Characteristic Control	no	yes	yes	yes	yes	yes
Entrepreneurial Firms Characteristic Control	no	yes	yes	yes	yes	yes
Entrepreneurial Firms Outcome Control	no	yes	yes	yes	yes	yes
Year fixed effect	no	yes	yes	no	no	no
County fixed effect	no	no	no	yes	no	no
VC firm fixed effect	no	no	yes	yes	no	no
VC firm * Industry fixed effect	no	no	no	no	no	yes
Industry fixed effect	no	no	no	no	yes	no
N	221319	147222	129883	158048	147222	128925
adj. R-sq	0.009	0.374	0.604	0.584	0.367	0.624

Table 7: Robustness for Hold-up hypothesis (Passive Outside Opportunity) for VC investment in the United States

The table below presents the results of the baseline regression analysis investigating the hold-up hypothesis for VC investment in the United States. The primary independent variable is the outside opportunities (passively), which measured using average SCI among the headquarter location of the entrepreneurs and that of the firms in the same industry. The dependent variable is the number of financing rounds with only inside VC investors. The analysis includes control variables at the industry level, such as average industry asset tangibility, average industry market-to-book ratio, and average industry RD ratio. Additionally, the regression incorporates VC characteristics variables, including the VC's total investment amount, VC age, and success rate. Firm characteristics considered are the number of VCs invested in, the number of financing rounds received in the initial round, and the total funds raised by the firm. Data regarding entrepreneurial firms and VC/PE firms are sourced from the Preqin database, while industry average data are obtained from Compustat. Heteroskedasticity-robust standard errors are reported in parentheses. Statistical significance is denoted by *, **, and *** at the 10%, 5%, and 1% levels, respectively.

	Number of Inside Financing Rounds					
	(1)	(2)	(3)	(4)	(5)	(6)
Outside Opportunity (Passively)	0.0815	0.0379	0.0117	0.0101	0.0335	0.0159
	(59.48)***	(5.76)***	(4.80)***	(2.03)**	(4.53)***	(2.45)**
Geographic Distance	0.524	0.195	-0.0451	-0.0636	0.250	0.0662
	(39.93)***	(4.27)***	(-1.56)	(-1.12)	(2.30)**	(0.71)
Number of Syndicated VC		-0.00974	-0.0112	-0.0191	-0.0201	-0.0195
		(-2.75)***	(-11.68)***	(-11.60)***	(-8.74)***	(-11.34)***
Industry Asset Intangibility		-0.373	-0.250	-0.211	-1.073	-1.050
		(-4.29)***	(-8.34)***	(-4.15)***	(-2.55)**	(-6.51)***
Industry Market to Book Ratio		-0.00000270	-0.00000568	-0.00000763	-0.000242	-0.000266
		(-0.03)	(-0.05)	(-0.07)	(-2.02)**	(-1.97)**
Industry R&D Ratio		0.0347	0.00220	0.0220	0.0530	0.0418
		(0.93)	(0.16)	(1.28)	(1.66)*	(2.43)**
Geographic Distance Control	yes	yes	yes	yes	yes	yes
Venture Characteristic Control	no	yes	yes	yes	yes	yes
Entrepreneurial Firms Characteristic Control	no	yes	yes	yes	yes	yes
Entrepreneurial Firms Outcome Control	no	yes	yes	yes	yes	yes
Year fixed effect	no	yes	yes	no	no	no
County fixed effect	no	no	no	yes	no	no
VC firm fixed effect	no	no	yes	yes	no	no
VC firm * Industry fixed effect	no	no	no	no	no	yes
Industry fixed effect	no	no	no	no	yes	no
N	319719	184370	173650	173652	184370	184370
adj. R-sq	0.020	0.147	0.278	0.268	0.156	0.414

Table 8: Baseline regression for Hold-up hypothesis (Proactive Outside Opportunity)

The table below presents the results of the baseline regression analysis investigating the hold-up hypothesis for VC investment in the United States. The primary independent variable is the outside opportunities (proactive), which measured using average SCI between the local headquarter location of entrepreneur and the SCI between the headquarter location of entrepreneurs and that of VC investors. The dependent variable is the number of financing rounds. The analysis includes control variables at the industry level, such as average industry asset tangibility, average industry market-to-book ratio, and average industry RD ratio. Additionally, the regression incorporates VC characteristics variables, including the VC's total investment amount, VC age, and success rate. Firm characteristics considered are the number of VCs invested in, the number of financing rounds received in the initial round, and the total funds raised by the firm. Data regarding entrepreneurial firms and VC/PE firms are sourced from the Preqin database, while industry average data are obtained from Compustat. Heteroskedasticity-robust standard errors are reported in parentheses. Statistical significance is denoted by *, **, and *** at the 10%, 5%, and 1% levels, respectively.

	Number of Financing Rounds					
	(1)	(2)	(3)	(4)	(5)	(6)
Outside Opportunity (Proactive)	0.0696	0.0283	0.0138	0.0146	0.0250	0.0217
	(33.70)***	(3.28)***	(4.20)***	(2.77)***	(2.33)**	(2.69)***
Geographic Distance	-0.0528	0.0288	0.00603	-0.000458	0.0143	-0.00348
	(-25.82)***	(5.76)***	(1.93)*	(-0.06)	(2.76)***	(-0.47)
Number of Syndicated VC		0.0824	0.0493	0.0283	0.0552	0.0189
		(5.96)***	(15.20)***	(7.50)***	(3.14)***	(4.54)***
Industry Asset Intangibility		-0.573	-0.384	-0.285	-3.255	-2.758
		(-2.34)**	(-5.95)***	(-3.04)***	(-2.56)**	(-8.65)***
Industry Market to Book Ratio		0.000172	0.000322	0.000246	-0.000403	-0.000436
		(0.66)	(1.02)	(0.74)	(-0.91)	(-1.47)
Industry R&D Ratio		-0.136	-0.167	-0.0816	0.166	0.122
		(-1.30)	(-3.16)***	(-1.76)*	(1.62)	(2.80)***
Geographic Distance Control	yes	yes	yes	yes	yes	yes
Venture Characteristic Control	no	yes	yes	yes	yes	yes
Entrepreneurial Firms Characteristic Control	no	yes	yes	yes	yes	yes
Entrepreneurial Firms Outcome Control	no	yes	yes	yes	yes	yes
Year fixed effect	no	yes	yes	no	no	no
County fixed effect	no	no	no	yes	no	no
VC firm fixed effect	no	no	yes	yes	no	no
VC firm * Industry fixed effect	no	no	no	no	no	yes
Industry fixed effect	no	no	no	no	yes	no
N	258604	147999	142401	142402	147999	147999
adj. R-sq	0.008	0.077	0.169	0.140	0.090	0.335

Table 9: State-level noncompete enforceability index and percentage of CEOs with NCAs

The table below presents the state-level noncompete enforcement index over the sample period from 1992 to 2014. The variable *Score* is the state-level noncompete enforcement score that takes a value between 0 and 12, where 0 is the weakest enforcement and 12 is the strictest.

State	Year Start	Year End	Score	%firm-year with NCA	Firm-year obs
AK	1992	2014	3	n/a	0
AL	1992	2014	5	70.06	177
AR	1992	2014	5	64.77	88
AZ	1992	2014	3	65.23	256
CA	1992	2014	0	41.01	2692
CO	1992	2011	2	50.18	277
CO	2012	2013	3	60	55
CO	2014		2	50.18	277
CT	1992	2014	3	65.31	490
DC	1992	2014	7	65.17	89
DE	1992	2014	6	16.28	86
FL	1992	1996	7	58	50
FL	1997	2014	9	64.34	603
GA	1992	2011	5	55.69	325
GA	2012	2014	6	68.33	60
HI	1992	2014	3	17.86	28
IA	1992	2014	6	28	100
ID	1992	2008	6	60	20
ID	2009	2014	7	40	10
IL	1992	2011	5	62.42	894
IL	2012	2013	6	71.68	113
IL	2014		5	62.42	894
IN	1992	2014	5	83.16	196
KS	1992	2014	6	59.8	102
KY	1992	2006	6	46.03	63
KY	2007	2014	8	71.26	87
LA	1992	2001	4	77.5	160
LA	2002	2003	0	80	15
LA	2004	2014	4	77.5	160
MA	1992	2014	6	65.49	849
MD	1992	2014	5	56.22	249
ME	1992	2014	4	68	50
MI	1992	2014	5	57.09	275
MN	1992	2014	5	71.81	376
MO	1992	2014	7	70.62	337
MS	1992	2014	4	46.48	71
MT	1992	2014	2	100	22
NC	1992	2014	4	62.96	378
ND	1992	2014	0	0	1
NE	1992	2014	4	60.94	64
NH	1992	2014	2	78.33	60
NJ	1992	2014	4	70.9	670
NM	1992	2014	2	9.52	21
NV	1992	2014	5	80.81	172
NY	1992	2014	3	64.61	1622

Continuation of Table 9					
State	**Year Start**	**Year End**	**Score**	**%firm-year with NCA**	**Firm-year obs**
OH	1992	2014	5	67.37	858
OK	1992	2014	1	45.22	115
OR	1992	2008	6	53.61	97
OR	2009	2014	7	77.19	57
PA	1992	2014	6	63.86	963
RI	1992	2014	3	78.26	46
SC	1992	2010	5	53.62	69
SC	2011	2014	4	33.33	24
SD	1992	2014	5	47.06	34
TN	1992	2014	7	67.18	326
TX	1992	1994	5	59.68	759
TX	1995	2006	3	65.86	290
TX	2007	2009	4	59.49	237
TX	2010	2011	5	59.68	759
TX	2012	2014	6	66.92	266
UT	1992	2014	6	71.43	91
VA	1992	2013	3	56.51	430
VA	2014		4	79.17	24
VT	1992	2014	5	65.22	23
WA	1992	2014	5	60.29	209
WI	1992	2009	3	56.61	189
WI	2010	2014	5	62.92	89
WV	1992	2014	2	12.9	31
WY	1992	2014	4	100	6

Table 10: Staggered Diff in Diff Regression on the Enforcement of NCAs

The table below presents the outcomes of a Staggered Difference-in-Differences (Diff-in-Diff) regression analysis, which examines the average treatment effect of NCA enforcement on the number of financing rounds for entrepreneurial firms situated in the treated states. Both the ETWFE and Callaway Sant'Anna estimation methods are employed. The treatment group consists of entrepreneurial firms located within the treated state for each event cohort, characterized by a NCA enforceability score exceeding 4 and a coverage ratio surpassing 40%. Conversely, the control groups, referred to as clean controls and encompassing the not-yet-treated observations, include all other firms located in state-years that did not experience such legal reforms. Panel A displays the average treatment effect of the treated group using the ETWFE estimator, while Panel B presents the average treatment effect of the treated group using Callaway and Sant'Anna estimators. The analysis does not incorporate any control variables. Data regarding entrepreneurial firms and VC/PE firms are sourced from the Preqin database, while industry-average data are obtained from Compustat. Heteroskedasticity-robust standard errors are reported in parentheses. Statistical significance is denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively.

JWDID		
Panel A	**John Woodridge ETWFE Estimator**	
	Never Treated as Control Group	**Not Yet Treated as Control Group**
	Number of Financing Round	**Number of Financing Round**
Average Treatment Effect on Treated	-0.669***	-0.652***
	(-65.51)	(-64.22)
Observations	306,874	306,874
R-squared	0.0415	0.0412

CSDID		
Panel B	**Callaway and Sant'ana Estimator**	
	Never Treated as Control Group	**Not Yet Treated as Control Group**
	Number of Financing Round	**Number of Financing Round**
Average Treatment Effect on Treated	-0.369***	-0.345***
	(-2.75)	(-2.69)
Observations	306,828	306,828
chi2(90)	1052.384	1043.527

Table 11: Second-Stage Regression Model: Instrumental Variable Approaches

The table below presents the outcomes of the second-stage regression employing instrumental variables to assess the hold-up hypothesis, specifically focusing on passive outside opportunities. The table consists of three columns. The first column represents the baseline regression without accounting for endogeneity control. The second column shows the results obtained using the instrumental variable of transportation cost dated back to 1920. Lastly, the third column shows the outcomes when utilizing the instrumental variable calculated without considering the railroad factor. The primary independent variable of interest is the measure of outside opportunities (passively), which measured using the average social connectedness index (SCI) between the headquarter locations of the entrepreneurs and those of firms within the same industry, and the interaction term between outside opportunities (passively) and the number of financing rounds. The analysis includes control variables at the industry level, such as average industry asset tangibility, average industry market-to-book ratio, and average industry R&D ratio. Additionally, the regression incorporates VC characteristics variables, including the VC's total investment amount, VC age, and success rate. Firm characteristics considered are the number of VCs invested in, the number of financing rounds received in the initial round, and the total funds raised by the firm. Data regarding entrepreneurial firms and VC/PE firms are sourced from the Preqin database, while industry average data are obtained from Compustat. Heteroskedasticity-robust standard errors are reported in parentheses. Statistical significance is denoted by *, **, and *** at the 10%, 5%, and 1% levels, respectively.

	Number of Financing Round		
	No IV	*Cost_1920*	*Cost_noRR*
OutsideOpportunity_Passive	0.016***	0.133***	1.799***
	(4.87)	(4.19)	(2.75)
Number of Syndicated VC	0.0208***	0.0196***	0.0143***
	(15.29)	(14.30)	(4.18)
Industry Asset Intangibility	-0.879***	-0.727***	-0.325
	(-4.41)	(-3.57)	(-0.75)
Industry Market to Book Ratio	-0.000311	-0.000285	-0.000670
	(-1.01)	(-0.90)	(-1.04)
Industry R&D Ratio	0.00449	0.00851	0.0396
	(0.25)	(0.47)	(1.04)
Venture Characteristic Control	yes	yes	yes
Geographic Distance Control	yes	yes	yes
Entrepreneurial Firms Characteristic Control	yes	yes	yes
Entrepreneurial Firms Outcome Control	yes	yes	yes
Year fixed effect	yes	yes	yes
County fixed effect	yes	yes	yes
VC firm * Industry fixed effect	yes	yes	yes
Industry fixed effect	yes	yes	yes
Adjusted R-squared	0.719	0.528	-0.862
Observations	125183	123091	123091

Table 12: The Effect of Staging (Hold-up - Passive outside Opportunity) on Post-Investment Performance of Entrepreneurial Firms

The table presented below provides the results of a logit regression analysis conducted to evaluate the performance of entrepreneurial firms Hold-up Hypothesis (Passive outside opportunity). The dependent variable is a dummy variable, denoted as the success exit, takes a value of 1 if the entrepreneurial firm achieves an IPO or successful acquisition, and 0 otherwise. The primary independent variable of interest is the measure of outside opportunities (passively), which measured using the average social connectedness index (SCI) between the headquarter locations of the entrepreneurs and those of firms within the same industry, and the interaction term between outside opportunities (passively) and the number of financing rounds. The analysis includes control variables at the industry level, such as average industry asset tangibility, average industry market-to-book ratio, and average industry RD ratio. Additionally, the regression incorporates VC characteristics variables, including the VC's total investment amount, VC age, and success rate. Firm characteristics considered are the number of VCs invested in, the number of financing rounds received in the initial round, and the total funds raised by the firm. Data regarding entrepreneurial firms and VC/PE firms are sourced from the Preqin database, while industry average data are obtained from Compustat. Heteroskedasticity-robust standard errors are reported in parentheses. Statistical significance is denoted by *, **, and *** at the 10%, 5%, and 1% levels, respectively.

	Success Exit									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Outside Opportunities (Passively)	0.0629	0.0432	0.00267	-0.00268	-0.0216	-0.0215	-0.0172	-0.0187	-0.0237	-0.0285
	(9.99)***	(5.41)***	(0.50)	(-0.23)	(-1.90)*	(-1.16)	(-2.91)***	(-1.75)*	(-2.30)**	(-2.48)**
Outside Opportunities (Passively)*Financing Rounds	0.0174	0.0203	0.00825	0.00905	0.00806	0.00863	0.00418	0.00474	0.00941	0.00801
	(33.42)***	(12.28)***	(7.63)***	(4.23)***	(3.67)***	(2.34)**	(3.36)***	(2.90)***	(4.26)***	(3.28)***
Number of Financing Rounds		-0.0302	-0.438	-0.398	-0.00442	-0.0806	0.531	0.528	-0.0519	0.130
		(-2.18)**	(-2.95)***	(-1.68)*	(-0.02)	(-0.25)	(2.33)**	(2.32)**	(-0.21)	(0.97)
Industry Average Geographic Distance		0.459	-0.113	-0.120	0.143	0.103	0.480	0.451	0.103	0.252
		(8.13)***	(-1.26)	(-0.77)	(1.02)	(0.68)	(3.18)***	(2.56)**	(0.78)	(9.69)***
Industry Average Geographic Distance * Financing Rounds			0.00212	0.00855	-0.0288	-0.0377	-0.182	-0.182	-0.0419	-0.0346
			(0.06)	(0.14)	(-0.61)	(-0.67)	(-3.13)***	(-3.87)***	(-0.88)	(-0.84)
Geographic Distance Control		yes	yes	yes	yes	yes	yes	yes	yes	yes
Venture Characteristic Control			yes	yes	yes	yes	yes	yes	yes	yes
Entrepreneurial Firms Characteristic Control			yes	yes	yes	yes	yes	yes	yes	yes
Entrepreneurial Firms Outcome Control			yes	yes	yes	yes	yes	yes	yes	yes
Year fixed effect				yes	yes			yes	yes	yes
County fixed effect									yes	yes
VC firm fixed effect					yes					
Industry fixed effect						yes			yes	
VC firm * Industry fixed effect							yes	yes		yes
N	39557	39557	19539	19532	15654	19451	7925	7919	19446	15586

Table 13: The Effect of Staging (Hold-up - Proactive outside Opportunity) on Post-Investment Performance of Entrepreneurial Firms

The table presented below provides the results of a logit regression analysis conducted to evaluate the performance of entrepreneurial firms on Hold-up Hypothesis (Proactive outside opportunity). The dependent variable is a dummy variable, denoted as the success exit, takes a value of 1 if the entrepreneurial firm achieves an IPO or successful acquisition, and 0 otherwise. The primary independent variable of interest is the measure of outside opportunities (proactive), which measured using the average SCI between the local headquarter location of entrepreneur and the SCI between the headquarter location of entrepreneurs and that of VC investors, and the interaction term between outside opportunities (proactive) and the number of financing rounds. The analysis includes control variables at the industry level, such as average industry asset tangibility, average industry market-to-book ratio, and average industry RD ratio. Additionally, the regression incorporates VC characteristics variables, including the VC's total investment amount, VC age, and success rate. Firm characteristics considered are the number of VCs invested in, the number of financing rounds received in the initial round, and the total funds raised by the firm. Data regarding entrepreneurial firms and VC/PE firms are sourced from the Preqin database, while industry average data are obtained from Compustat. Heteroskedasticity-robust standard errors are reported in parentheses. Statistical significance is denoted by *, **, and *** at the 10%, 5%, and 1% levels, respectively.

	Success Exit									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Outside Opportunities (Proactive)	-0.00712	-0.00434	-0.0191	-0.0228	-0.0326	-0.0338	-0.0191	-0.0204	-0.0355	-0.0357
	(-1.61)	(-0.68)	(-3.86)***	(-2.02)**	(-3.27)***	(-1.95)*	(-3.11)***	(-1.94)*	(-5.35)***	(-3.11)***
Outside Opportunities (Proactive)*Financing Rounds	0.0149	0.0148	0.00853	0.00933	0.00855	0.00856	0.00366	0.00420	0.00916	0.00827
	(34.72)***	(10.11)***	(8.62)***	(5.43)***	(5.11)***	(2.72)***	(3.00)***	(2.81)***	(5.97)***	(3.14)***
Number of Financing Rounds		0.00495	-0.00792	-0.0120	-0.0122	-0.00568	0.0185	0.0170	-0.00867	-0.0121
		(0.33)	(-0.93)	(-0.87)	(-1.05)	(-0.35)	(1.97)**	(1.84)*	(-1.10)	(-1.20)
Geographic Distance		0.0410	0.0502	0.0475	0.0383	0.0445	0.0184	0.0194	0.0429	0.0393
		(8.77)***	(6.42)***	(4.49)***	(3.09)***	(3.71)***	(1.79)*	(1.67)*	(3.74)***	(4.08)***
Geographic Distance * Financing Rounds			-0.00914	-0.00856	-0.00769	-0.00795	-0.00533	-0.00488	-0.00729	-0.00688
			(-5.80)***	(-4.92)***	(-3.25)***	(-3.95)***	(-2.51)**	(-2.32)**	(-3.34)***	(-2.41)**
Geographic Distance Control		yes	yes	yes	yes	yes	yes	yes	yes	yes
Venture Characteristic Control			yes	yes	yes	yes	yes	yes	yes	yes
Entrepreneurial Firms Characteristic Control			yes	yes	yes	yes	yes	yes	yes	yes
Entrepreneurial Firms Outcome Control			yes	yes	yes	yes	yes	yes	yes	yes
Year fixed effect				yes	yes			yes	yes	yes
County fixed effect									yes	yes
VC firm fixed effect					yes					
Industry fixed effect						yes			yes	
VC firm * Industry fixed effect							yes	yes		yes
N	39603	32948	19558	19551	15674	19467	7926	7920	19462	15604

Table 14: The Effect of Staging (Hold-up-Passive outside Opportunity with only inside VC investors) on Post-Investment Performance of Entrepreneurial Firms

The table presented below provides the results of a logit regression analysis conducted to evaluate the performance of entrepreneurial firms Hold-up Hypothesis (Passive outside opportunity) for inside VC investors only. The dependent variable is a dummy variable, denoted as the success exit, takes a value of 1 if the entrepreneurial firm achieves an IPO or successful acquisition, and 0 otherwise. The primary independent variable of interest is the measure of outside opportunities (passively), which measured using the average social connectedness index (SCI) between the headquarter locations of the entrepreneurs and those of firms within the same industry, and the interaction term between outside opportunities (passively) and the number of inside financing rounds. The analysis includes control variables at the industry level, such as average industry asset tangibility, average industry market-to-book ratio, and average industry R&D ratio. Additionally, the regression incorporates VC characteristics variables, including the VC's total investment amount, VC age, and success rate. Firm characteristics considered are the number of VCs invested in, the number of financing rounds received in the initial round, and the total funds raised by the firm. Data regarding entrepreneurial firms and VC/PE firms are sourced from the Preqin database, while industry average data are obtained from Compustat. Heteroskedasticity-robust standard errors are reported in parentheses. Statistical significance is denoted by *, **, and *** at the 10%, 5%, and 1% levels, respectively.

	Success Exit							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Social Connectedness Index	0.0873	0.0904	0.0145	0.0133	-0.00383	-0.0103	-0.00983	-0.0116
	(13.83)***	(12.44)***	(3.20)***	(1.60)	(-0.48)	(-1.38)	(-2.27)**	(-1.42)
SCI*Number of Financing Inside Rounds	0.0304	0.0167	0.00982	0.00928	0.00622	0.00930	0.00923	0.00628
	(20.82)***	(5.12)***	(5.17)***	(3.12)***	(2.28)**	(2.67)***	(4.22)***	(1.97)**
Number of Financing Inside Rounds		0.0883	-0.0338	-0.0724	0.203	0.246	0.278	0.238
		(4.14)***	(-0.12)	(-0.17)	(0.61)	(0.60)	(0.84)	(0.81)
Geographic Distance		0.550	0.194	0.170	0.230	0.281	0.286	0.286
		(9.83)***	(2.20)**	(1.03)	(1.66)*	(2.35)**	(3.22)***	(4.68)***
Geographic Distance * Financing Rounds			0.00212	0.00855	-0.0288	-0.0377	-0.0419	-0.0346
			(0.06)	(0.14)	(-0.61)	(-0.67)	(-0.88)	(-0.84)
Geographic Distance Control	no	yes	yes	yes	yes	yes	yes	yes
Venture Characteristic Control	no	no	yes	yes	yes	yes	yes	yes
Entrepreneurial Firms Characteristic Control	no	no	yes	yes	yes	yes	yes	yes
Entrepreneurial Firms Outcome Control	no	no	yes	yes	yes	yes	yes	yes
Year fixed effect	no	no	no	yes	yes	no	yes	yes
County fixed effect	no	no	no	no	no	no	yes	yes
VC firm fixed effect	no	no	no	no	yes	no	no	no
Industry fixed effect	no	no	no	no	no	yes	yes	no
VC firm * Industry fixed effect	no	no	no	no	no	no	no	yes
N	39557	39557	19539	19532	15654	19451	19446	15586

8 Online Appendix

Figures

Figure 5: .

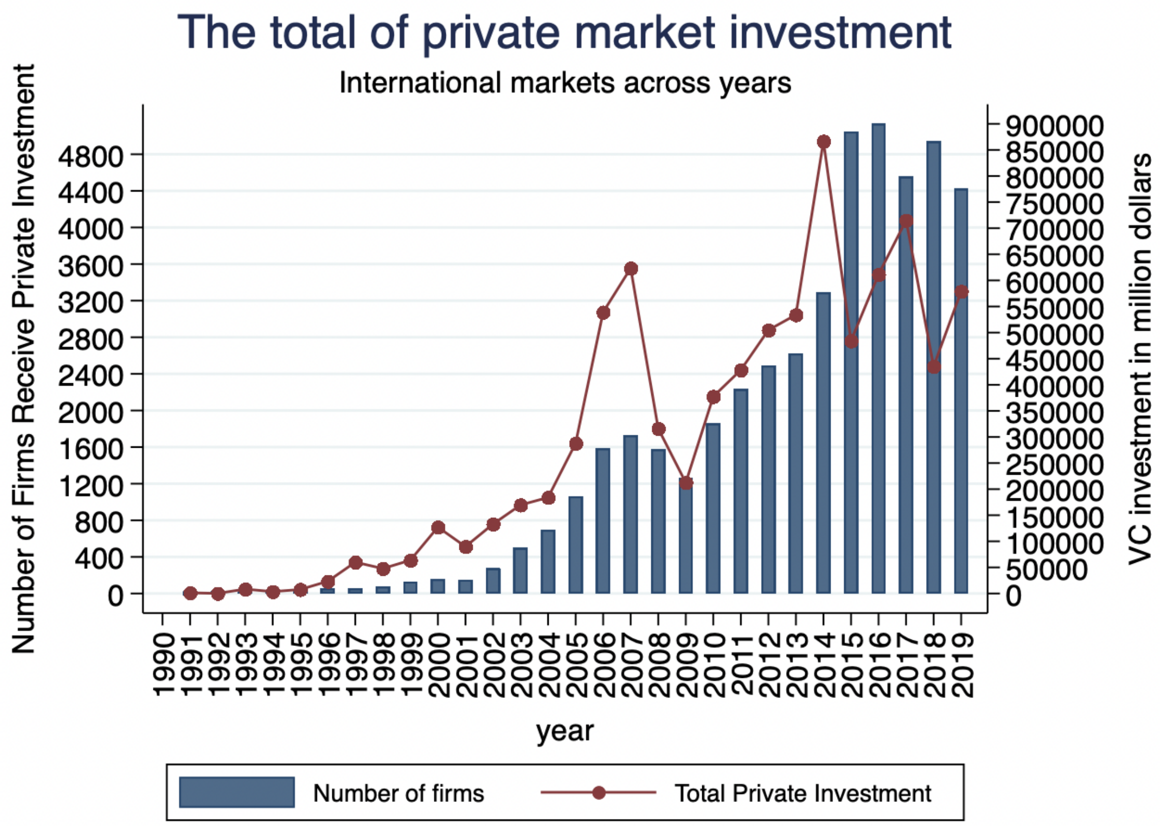


Figure 6: .

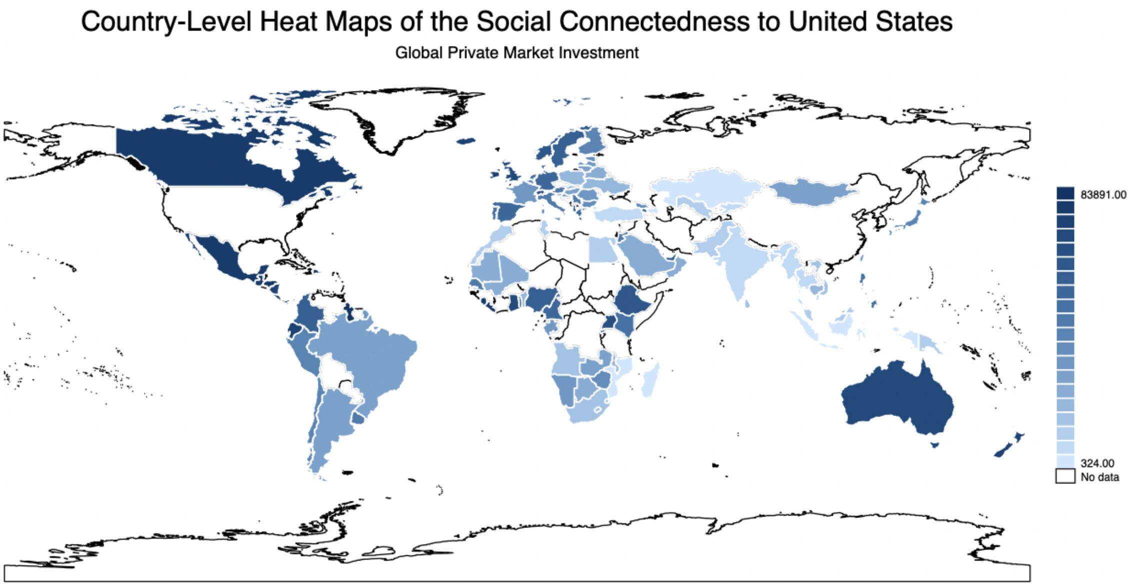
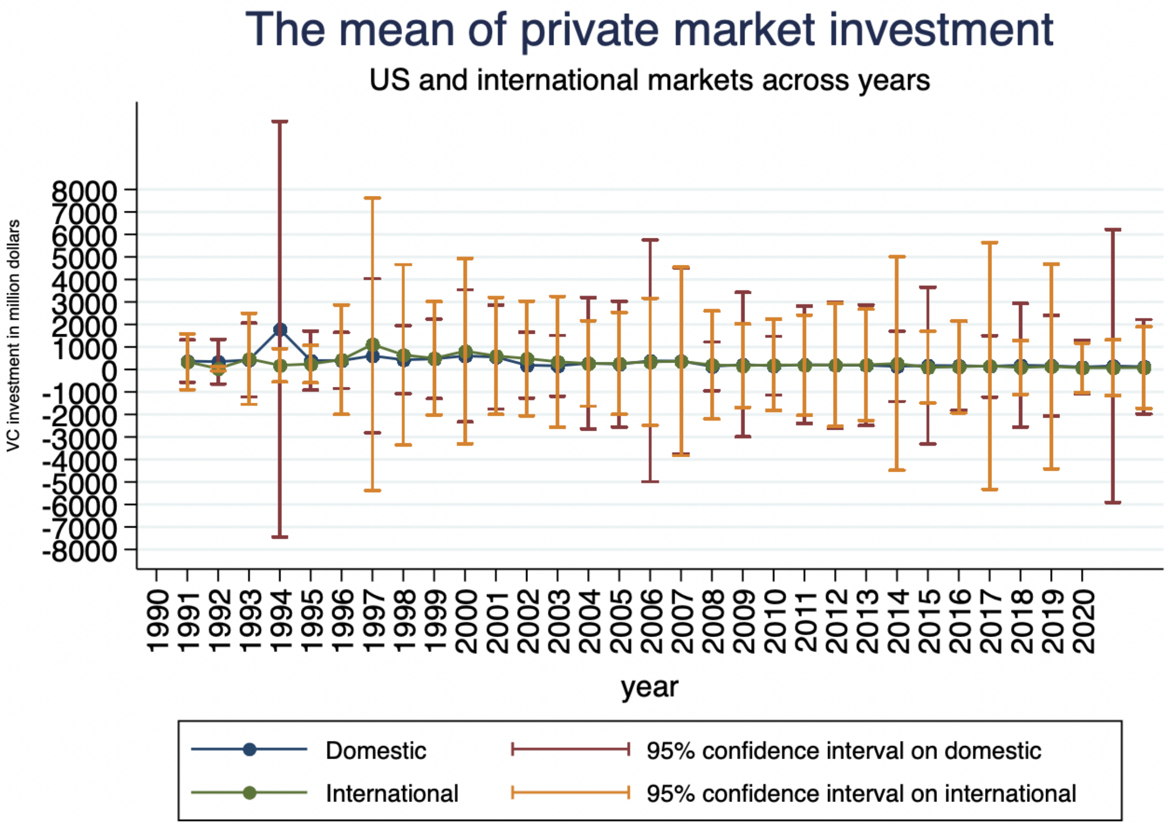
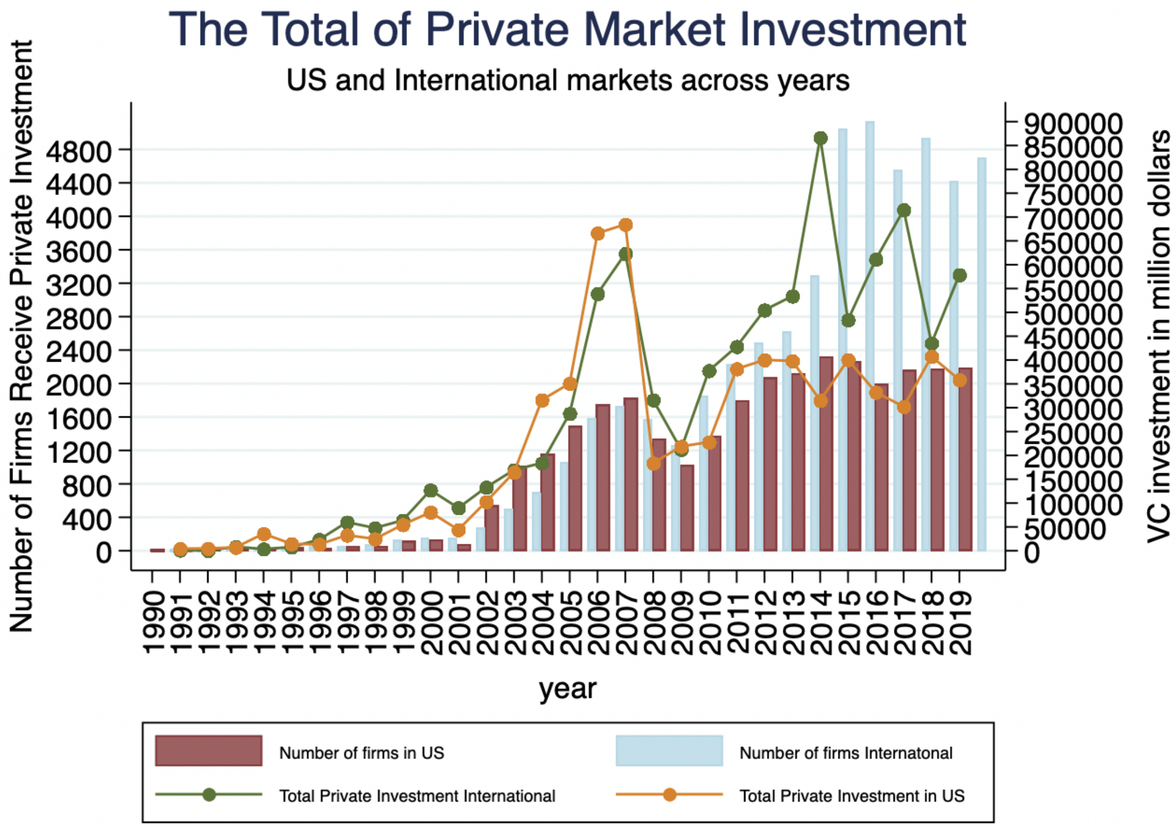

Country-Level Heat Maps of the Social Connectedness to United States
Global Private Market Investment
83891.00
324.00
No data

Figure 7: .



The mean of private market investment
US and international markets across years
VC investment in million dollars
8000
7000
6000
5000
4000
3000
2000
1000
0
-1000
-2000
-3000
-4000
-5000
-6000
-7000
-8000
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
year
Domestic
International
95% confidence interval on domestic
95% confidence interval on international

Figure 8: .



The Total of Private Market Investment
US and International markets across years
Number of Firms Receive Private Investment
VC investment in million dollars
0
400
800
1200
1600
2000
2400
2800
3200
3600
4000
4400
4800
0
50000
100000
150000
200000
250000
300000
350000
400000
450000
500000
550000
600000
650000
700000
750000
800000
850000
900000
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
year
Number of firms in US
Number of firms Internatonal
Total Private Investment International
Total Private Investment in US

Figure 9: .

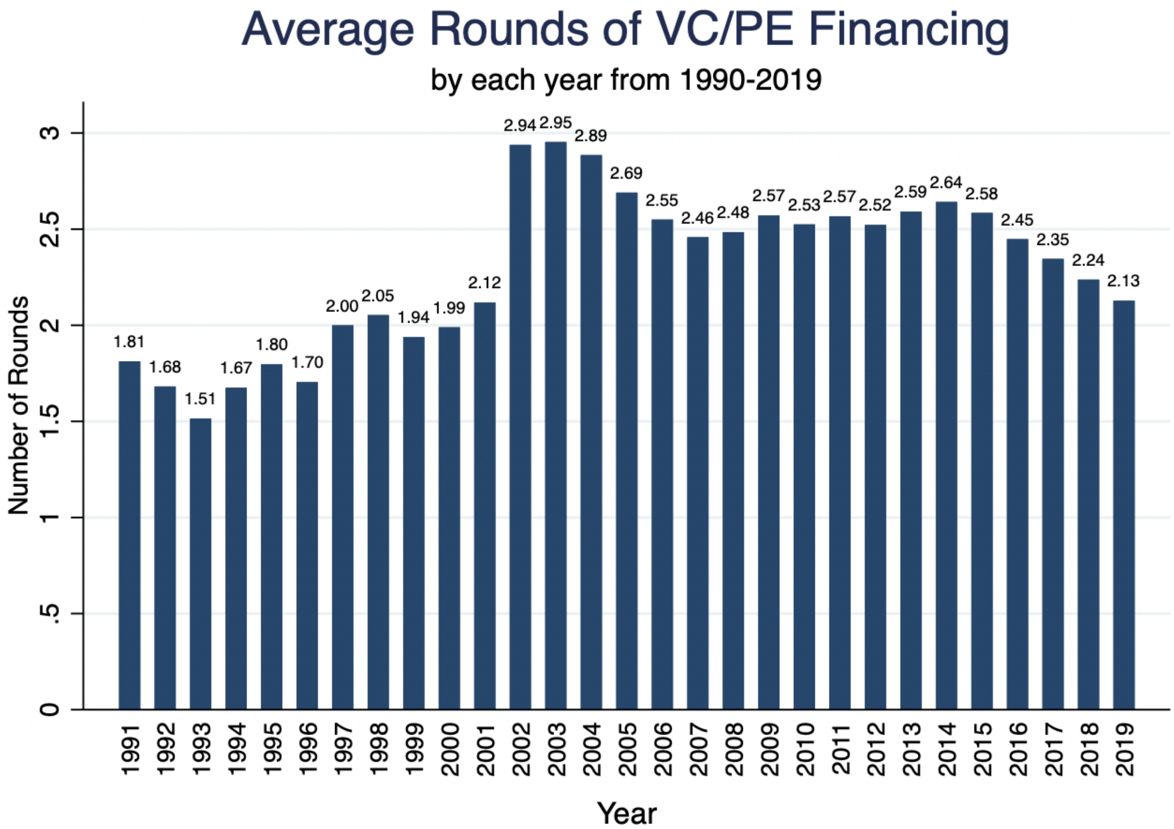

Average Rounds of VC/PE Financing
by each year from 1990-2019
Number of Rounds
0
.5
1
1.5
2
2.5
3
1.81
1.68
1.51
1.67
1.80
1.70
2.00
2.05
1.94
1.99
2.12
2.94
2.95
2.89
2.69
2.55
2.46
2.48
2.57
2.53
2.57
2.52
2.59
2.64
2.58
2.45
2.35
2.24
2.13
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
Year

Figure 10: .

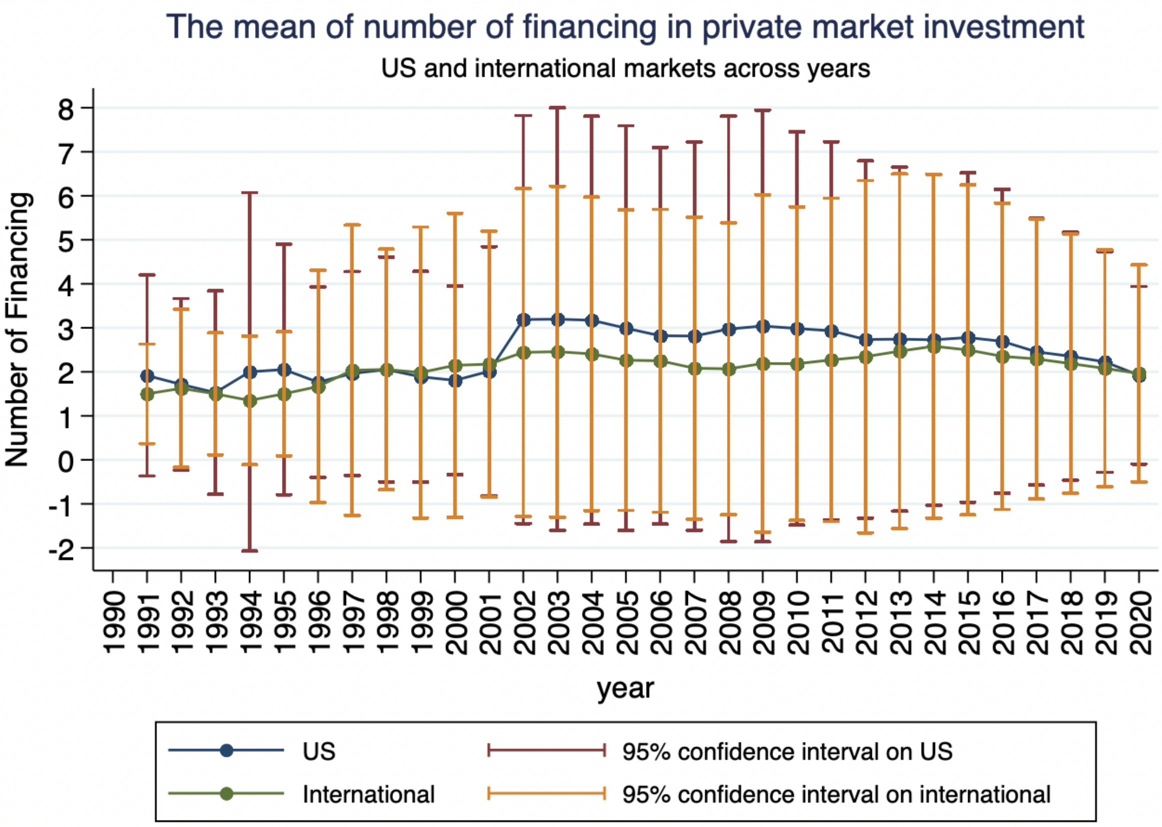
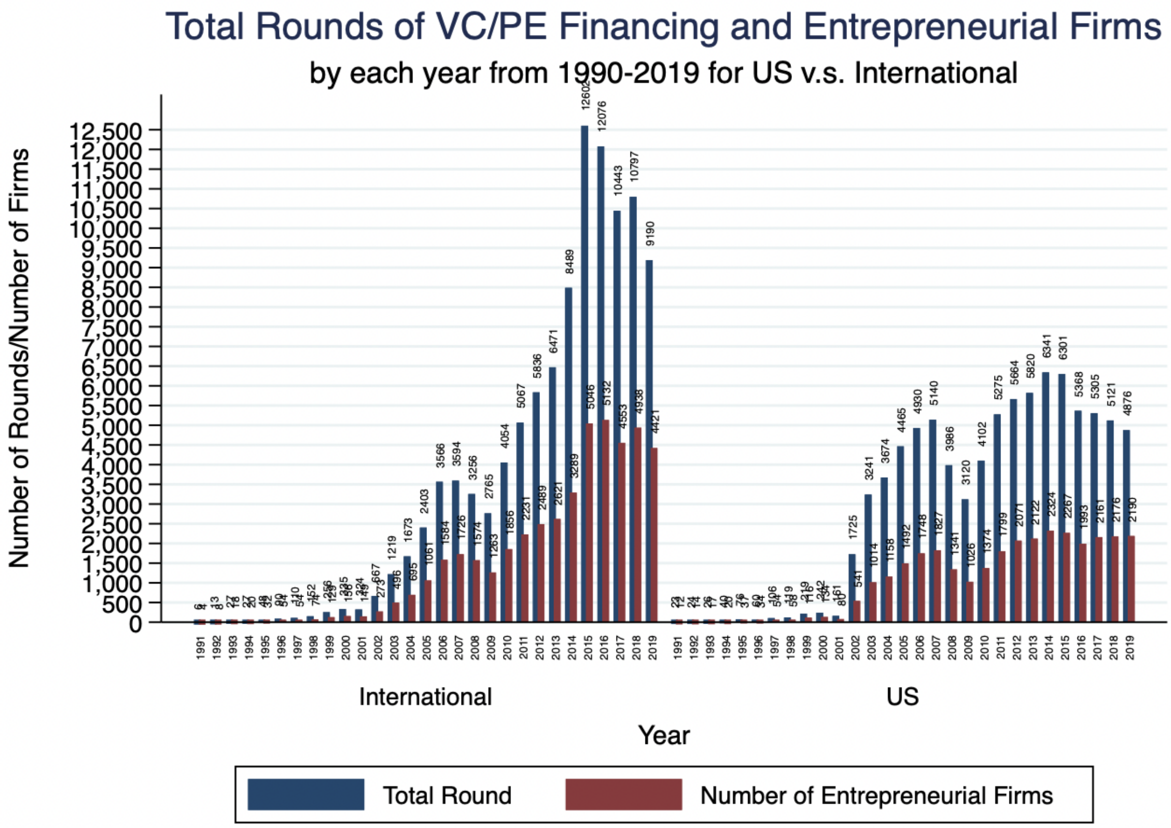
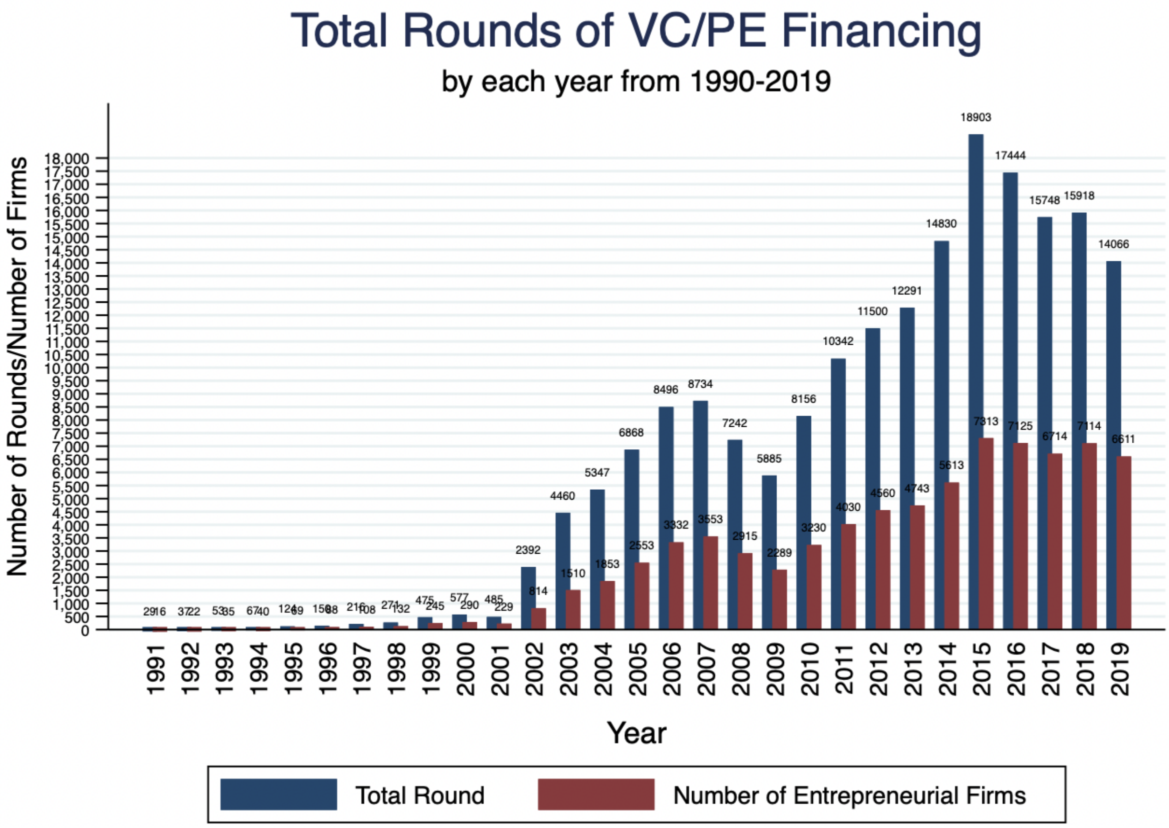

The mean of number of financing in private market investment
US and international markets across years
Number of Financing
8
7
6
5
4
3
2
1
0
-1
-2
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
year
US
95% confidence interval on US
International
95% confidence interval on international

Figure 11: .



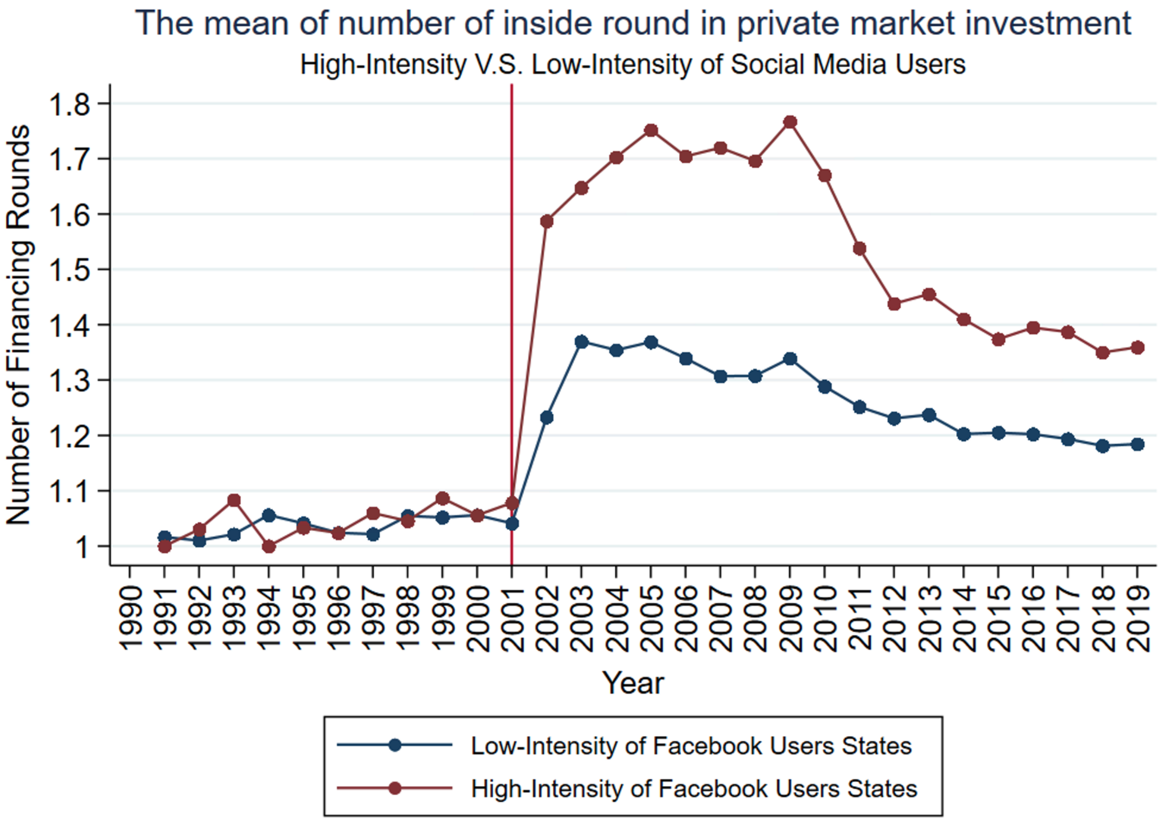
Total Rounds of VC/PE Financing and Entrepreneurial Firms
by each year from 1990-2019 for US v.s. International
Number of Rounds/Number of Firms
International
US
Year
Total Round
Number of Entrepreneurial Firms

Figure 12: .



Total Rounds of VC/PE Financing
by each year from 1990-2019
Number of Rounds/Number of Firms
Year
Total Round
Number of Entrepreneurial Firms

Figure 13: .



The mean of number of inside round in private market investment
High-Intensity V.S. Low-Intensity of Social Media Users
Number of Financing Rounds
1.8
1.7
1.6
1.5
1.4
1.3
1.2
1.1
1
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
Year
Low-Intensity of Facebook Users States
High-Intensity of Facebook Users States