How Does Active Involvement Benefit Investors? Evidence from 85 Billion Cell Phone Signals

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Abstract

I investigate the reputation effects of active involvement, specifically examining how venture capitalists' (VCs') on-site meetings with portfolio companies affect VCs' reputations and future deal flow. By analyzing cell phone signals collected around VC and startup office buildings from 2018 to 2023, I measure VCs' involvement intensity and deal flow quality. Using exogenous variation in travel ease, I show that increased VC involvement leads them to receive better online reviews from entrepreneurs, attracting more and higher-quality new entrepreneurs to pitch, ultimately improving future investment outcomes. Furthermore, I document six stylized facts about VC involvement: (1) VCs visit underperforming portfolio companies more frequently; (2) the frequency of visits increases when portfolio companies are closer; (3) early-stage investments receive more frequent visits; (4) VCs and nontraditional investors (CVCs, PEs, hedge funds) visit at similar frequencies, while accelerators and incubators visit more often; (5) deals with more co-investors involve more overall visits, but each investor visits less frequently; and (6) larger VCs visit less frequently per deal.

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1. Introduction

In many asset classes, investors actively engage after investing to help and add value to the companies they have invested in. In venture capital, 98% of investors interact with their portfolio companies at least once a month (Gompers et al. (2020)), and such active involvement is similarly common in buyouts (Gompers et al. (2016)) and private debt (Block et al. (2024)). Although previous research has shown the direct benefits of active involvement for portfolio companies (Bernstein et al. (2016)), little is known about the indirect reputational benefits for investors. In this paper, I show that by actively helping portfolio companies, investors can enhance their reputations and attract better deal flow in the future. The main contributions of this paper are constructing the first empirical measure of active involvement, showing its indirect reputational benefits, and providing several stylized facts about active involvement.

In this paper, I use the VC industry as a laboratory to explore how active involvement affects investors' reputations and future deal flow. In venture capital, active involvement refers to value-adding services, with the most common form being regular meetings with portfolio companies to offer strategic advice. While many anecdotes[1] suggest that the VC industry is well suited for studying how active involvement affects future deal flow, empirically identifying this causal relation is challenging. There are three main challenges. First, measuring VC involvement is difficult, as meetings with portfolio companies typically occur off the record. Second, VC deal flow is similarly hard to measure. Lastly, active involvement is endogenous.

To address the first empirical challenge, I analyze 85 billion cell phone signals near VC and startup offices from January 2018 to January 2023 to construct the first empirical measure of VCs' involvement intensity. This novel dataset includes cell phone location information with timestamps, recorded whenever an app is active or running in the background. While this anonymized dataset fully complies with legal standards and contains no individually identifiable information, it still enables the construction of a measure for identifying potential meetings between VCs and their portfolio companies. From this raw data, I construct a measure of VC involvement in two steps. First, I determine if a device likely belongs to

[1] The VC industry is suitable for studying how active involvement impacts deal flow for three reasons: first, active involvement is a core focus for VCs themselves. Bill Gurley, a general partner at Benchmark, said, "We view ourselves as a services firm. We practice the art of adding value, and we try to earn our reputation and brand every day" (Janz, 2015). Second, active involvement is crucial for securing future deal flow. According to the Forward Partners' survey in 2021 (Forward Partners, 2021), over half of startup founders consider value-add more important than a VC's track record when choosing a VC. Lastly, VCs view deal flow as key to their success. As Chris Dixon, General Partner at Andreessen Horowitz, puts it, "Success

a VC employee. As a baseline, I define an employee's device as one that appears within 200 meters of the VC building for at least five working days in a month and is observed for at least two months. To further differentiate VC employees from other frequent visitors like delivery workers, I set a filter to exclude those counted as employees at more than five companies. Second, I define a meeting as an event where a potential VC employee appears within 200 meters of a portfolio company's office building during working hours and stays there for at least 30 minutes. These steps help distinguish VC-related visits from random passersby. I show that the main results are robust to variations in construction methods. To address potential concerns about tall buildings housing multiple companies, I construct a subsample that excludes any building shared by multiple companies, serving as additional robustness checks. Overall, I gather cell phone signals for more than 10,000 investors (including VCs, PEs, CVCs, accelerators, incubators, and angel investors) and over 30,000 associated portfolio companies' office buildings from 2018 to 2023. This dataset captures the monthly meeting frequency for over 150,000 deals.

To address the second empirical challenge, I develop a proxy for VC deal flow using the same data source. Unlike public equity markets, where investors can invest in any listed stock, VCs are limited to selecting startups from their available choice set (deal flow) — specifically, from entrepreneurs who are willing to pitch and potentially accept funding. Ideally, the measure for VC deal flow would be a comprehensive list of entrepreneurs *willing to pitch* to each VC. However, obtaining such a list from every VC in the industry is not feasible. Instead, a practical proxy is the list of entrepreneurs who *have pitched* to each VC firm. Using the same data-construction methods and filters as in the baseline, I identify cell phones that likely belong to startup employees. Next, I identify pitch events as cases where a potential startup employee visits the VC building for more than 30 minutes. The group of startups that pitched to the VC is then used as a proxy for the VC's deal flow in a given month.

The last empirical challenge arises from the endogeneity of VC involvement. Omitted variables, such as the time-varying reputation and expertise of the VC, could influence both the frequency of their visits to portfolio companies and their subsequent deal flow. I address this challenge using an instrumental variable computed from the cell phone data. I use the number of people (excluding VC and startup employees) who happen to pass near both the VC's and the portfolio company's buildings in a given month as an instrumental variable for the intensity of VC involvement for that pair during that month[2]. The intuition is that

in VC is probably 10% about picking, and 90% about sourcing the right deals and having entrepreneurs choose your firm as a partner"(Eisenmann and Kind (2014)).

[2]To ensure that the correlation between the IV and involvement intensity isn't driven by mistakenly

the realized traveling population between the two buildings in a month acts as a proxy for how convenient it is to travel between them, and when travel is easier, VCs tend to visit the portfolio companies more frequently. The first-stage regression results support the relevance condition, showing that the monthly number of passersby strongly predicts the frequency of VC-portfolio company meetings, with F-statistics well above 10.

The IV likely satisfies the exclusion restriction, because these passersby (who are not VC or startup employees) are random individuals traveling in the vicinity and have no direct relevance to the VCs or portfolio companies. Therefore, the number of passersby — serving as an indicator of travel ease between a VC and a portfolio company's locations — is unlikely to affect the VC's future deal flow through any other channel. However, to argue that this IV is valid, it's essential to ensure that the number of passersby is not correlated with unobserved factors that might influence both VC involvement and future deal flow. A plausible concern is the effect of local shocks, such as a local economic boom near the VC. For instance, a thriving local economy could simultaneously improve the VC's subsequent deal performance and increase the number of passersby, leading to a spurious result. However, since the IV captures travel ease at the VC-portfolio company pair by month level, I can control for such local shocks. Specifically, I include both VC city by month and portfolio company city by month fixed effects to control for any local shocks in the VC's or portfolio company's areas (including COVID). Additionally, I incorporate VC-portfolio company pair fixed effects to control for the distance between buildings and other deal-level characteristics. This approach strengthens the argument for the exclusion restriction of the IV.

Utilizing a two-stage least squares (2SLS) regression, I examine the reputation effect of VC involvement and document three main findings. First, I find that increased VC involvement leads to improved future deal flow. Specifically, if a VC increases meeting frequency with all existing portfolio companies in a month by 10%, then this VC can attract 1 more entrepreneur pitching per month over the next six months (i.e., a 16% increase in deal flow size). Moreover, the ex-post quality of these pitching entrepreneurs appears to be higher, with their average unicorn rate increasing by 0.27 percentage points (i.e., a 7% increase in the unicorn rate). However, the effects on deal flow appear to be short-term: both the quantity and quality of pitching startups significantly increase in the first 6 months, but gradually diminish over longer horizons (such as 12, 18, and 24 months). Why does helping existing

counting VC employees as passersby, I distinguish between cell phone signals collected on weekdays and weekends. Specifically, the baseline IV is based on cell phone signals captured during non-working hours and weekends from individuals unaffiliated with either VCs or startups. This contrasts with the VC involvement measure, which is constructed using cell phone signals from likely VC employees during regular working hours. In the robustness checks, I also include weekdays when constructing the IV, and the main results remain consistent.

portfolio companies more often lead to better deal flow in the short term? One potential explanation is that the portfolio companies receiving help are likely to recommend their VCs to other startups. This mechanism is short-term because portfolio companies are more likely to recall recent help but are less likely to remember a VC's visit from several years ago. Anecdotally, VC-backed entrepreneurs commonly share word-of-mouth recommendations.[3] A subsample test supports this word-of-mouth recommendation hypothesis. Specifically, I find that the effects on deal flow are more pronounced in the subsample where both the existing portfolio company that received help and the future pitching startups are located in the same state, making communication between the two startups more likely. In contrast, the effects are less significant in the subsample where they are located in different states, making communication between them less likely.

Second, I find that increased VC involvement leads to better reviews from entrepreneurs. I collect entrepreneurs' reviews of venture capitalists from over 2,000 entries on "VC Guide," spanning from 2020 to 2023. This "VC Guide" website, often referred to as the "Glassdoor for VCs," regularly invites founders to anonymously share their experiences and reviews of their VC investors. Entrepreneurs are encouraged to leave overall ratings and specific feedback on VCs' value-adding contributions. In IV regressions, I find that if a VC increases meeting frequency with all existing portfolio companies by 10%, then the VC's review rating increases by 0.37 on a 10-point scale (i.e., a 5% increase in rating). Overall, these findings suggest that entrepreneurs generally prefer VCs who visit and help more often.

Lastly, I document that increased VC involvement enhances the likelihood of VCs investing in unicorns in the future. Specifically, if a VC increases meeting frequency with all existing portfolio companies by 10%, the new investments the VC makes over the next 6 to 24 months have a 0.29 percentage point higher chance of becoming unicorns (i.e., an 8% increase in the unicorn rate of future investments). Interestingly, this magnitude is very similar to the improvement in deal flow quality, as the unicorn rate of pitching startups over the first 6 months is 0.27 percentage points higher. This alignment likely suggests that the enhanced quality of deal flow may be the primary driving force behind the observed improvement in the VC's future investment outcomes. To further compare this indirect reputational benefit to the direct benefit, I test the direct benefit and find that more involvement leads

[3] Founders often talk to existing portfolio companies before choosing an investor. As TDK Ventures' report (TDK Ventures, 2024) notes, "Founders are increasingly turning the table and conducting their own reference checks and diligence on VCs – including on the latter's failed investments." VCs themselves encourage founders to speak with their existing portfolio companies before taking the VCs' money. For example, Fred Wilson, co-founder of Union Square Ventures, said, "Instead of references, I like to give a list of every entrepreneur I've ever worked with and an email address. I tell them, 'Throw a dart at that list and talk to four or five of them randomly'"(Suster, 2010).

to a higher unicorn rate for the focal portfolio companies, consistent with Bernstein et al. (2016). I also conduct a simple back-of-the-envelope calculation of the magnitude and find that indirect benefits are just as important as direct ones.

Overall, the three main results likely illustrate the following reputation effect of active involvement: by actively helping portfolio companies, VCs build their reputation for adding value, as evidenced by higher review ratings. This enhanced reputation helps VCs secure better deal flow, which eventually leads to improved investment performance.

In addition to the main findings, the paper documents six stylized facts about VC involvement. For example, I show that VCs visit underperforming companies more often. The previous results help explain why. Even though the underperforming company will probably not deliver much profit to the VC, helping that company can improve the VC's reputation and future deal flow. As the dataset includes detailed active involvement activity across 150,000 deals over a span of five years, these descriptive results are likely representative of the VC industry in the U.S.

The paper is related to several strands of the literature. First, by constructing the first direct measure of VC active involvement, it contributes to the extensive body of work on VCs' active involvement. Early studies, such as Sahlman (1990) and Gorman and Sahlman (1989), offer descriptive insights into how VCs spend significant time mentoring founders and providing strategic guidance. Hsu (2004), using hand-collected data from startups with multiple VC offers, shows that entrepreneurs prefer higher-reputation VCs, in spite of their worse deal terms, likely because these VCs add more value through their active involvement. Building on these insights, several studies examine VC involvement in CEO replacements within portfolio companies (Lerner (1995); Hellmann and Puri (2002); Wasserman (2003); Kaplan et al. (2012)). Another line of research explores how VC value-adding activities impact portfolio company performance, particularly their likelihood of successful exits. Bottazzi et al. (2008) find that VC involvement is positively related to the success of portfolio companies. One challenge in this literature is disentangling selection effects from treatment effects. To address this, Sørensen (2007) employs a two-sided matching model to estimate the relative importance of VC value-adding versus screening. Bernstein et al. (2016) rules out selection effects by exploiting a novel exogenous source of variation in involvement: the introduction of new airline routes that reduce VCs' travel times to their existing portfolio companies. This paper builds on these studies by directly measuring active involvement and focusing on the indirect reputational benefits to investors, rather than the direct benefits to portfolio companies.

This paper also contributes to the growing literature on VC deal flow. Nanda et al. (2020) find that the success of a VC's first 10 investments predicts later success, suggesting that early wins improve access to deal flow, leading to higher-quality investments. Cong and Xiao (2022) develop a theoretical framework showing how deal flow can perpetuate luck. This paper adds to this literature by offering the first direct measure of VC deal flow.

Finally, this paper contributes to a large, mostly theoretical literature that explores how reputation concerns motivate financial intermediaries to put in costly efforts for long-term benefits. The idea of reputation effects in dynamic games with incomplete information stems from Kreps and Wilson (1982), Milgrom and Roberts (1982), and Holmstrom (1982). Building on this, several classic finance theory papers model how reputation acquisition reduces moral hazard in the context of financial intermediaries. Chemmanur and Fulghieri (1994) model how reputation concerns push investment banks to set strict standards in evaluating firms—taking on short-term costs for long-term gains. Pichler and Wilhelm (2001) show how reputation helps reduce free-riding in investment banking syndicates. More recently, Hartman-Glaser (2017) examines how reputation influences banks' decisions to retain portions of the loans they create, while Winton and Yerramilli (2021) model how reputation concerns motivate banks to keep monitoring loans they've sold. However, evidence supporting these theories is scarce, likely due to challenges in measuring intermediaries' costly efforts and reputation, as well as in identifying causal relations. This paper takes a step toward addressing these challenges and contributes to the literature by empirically testing this important class of theories.

The structure of this paper is as follows: Section 2 discusses the data and key variables. Section 3 presents stylized facts about active involvement. Section 4 describes the empirical strategy. Section 5 shows the three main results. Section 6 tests the robustness of the main results. Section 7 concludes.

2. Data

2.1. Independent Variable and Sample Selection

To measure VC active involvement, I analyze cell phone signals within a 200-meter radius around VC and startup office buildings from January 2018 to January 2023. The cell phone signal dataset is used in various industries to understand user behaviors and improve sales performance. Smartphone operating systems (Android and iOS) record the longitude and latitude of a cell phone with timestamps every 5 to 10 minutes, and more frequently when the user is driving. These location estimates can be accurate within 20 meters, and subject to user permissions, are shared with open or backgrounded apps. The data vendor collects this location data from hundreds of popular apps in app stores, spanning a variety of categories, including messaging, social media, navigation, music, photo, weather, travel, health and fitness, and eight other categories. The data provider reports coverage of 220 to 240 million monthly active users in the U.S., which represent roughly 80% of all smartphones.[4]

Since smartphones can be turned off, lose reception, or have relevant apps neither open nor running in the background, there's no guarantee that every meeting will be captured. However, because this measurement error is determined by individual cell phone usage habits (such as how often someone clears background apps), it should not be correlated with specific VC or startup characteristics, which suggests that the measurement error is unlikely to introduce bias into the results.

To construct the dataset, I capture all cell phone signals near VC and startup office buildings. Using the Google Maps API, I convert the addresses of the VC and startup offices into corresponding coordinates. This allows me to calculate the distance between each signal and the office buildings. For the baseline regression, I use a 200-meter cutoff. Signals beyond this range are discarded, while those within are retained. I further test the data in robustness checks by adjusting the cutoff to 100 meters and 50 meters.

The construction of the dataset progresses through two main phases. First, I aim to identify devices likely belonging to VC employees. To differentiate VC employees from passersby, I consider the frequency and timing of a device's appearance near the VC office. I assume that an employee's device is frequently detected near the office during standard working hours, typically from 8 am to 5 pm. Since a typical month has around 20 working days, a device detected in the vicinity of the VC office for more than 5 working days per month and lasting for at least two months is flagged as likely belonging to an employee. For additional verification, I also apply alternative criteria of 10 and 15 working days per month for 1 to 3 months, and the results for these alternative filters are shown in Section 6. To further differentiate VC employees from frequent visitors like delivery workers, I set a filter to exclude those counted as employees at more than five companies.

Second, to detect potential meetings between VCs and their portfolio companies, I use the duration of a device's presence near a portfolio company's office as a key filter. If a potential VC employee device is detected within 200 meters of a portfolio company's office during

[4]According to a 2023 Pew Research Center report (see `https://www.pewresearch.org/internet/fact-sheet/mobile/`), 90% of U.S. adults report owning a smartphone, and the U.S. population is approximately 335 million in 2023, so the number of smartphone users is approximately 300 million.

working hours and stays there for at least 30 minutes, I consider it a potential meeting.

To address further concerns, I run two subsample tests in Section 6. First, the active involvement measure can be misleading if several portfolio companies of the same VC have the same office address, which is likely when early-stage startups share the same incubator. To resolve this issue, I construct a subsample to exclude buildings with multiple startups. Second, during COVID, many meetings moved online, and the VC-startup pairs that still had on-site meetings might have specific characteristics, potentially leading to sample selection bias. To address this concern, I run a subsample from January 2018 to January 2020, just before COVID, when most meetings were on-site. I report the main results for these two robustness checks in Section 6. All the robustness checks yield results similar to those of the baseline.

Using the data-construction method described above, I can recover the involvement intensity for all recorded deals in PitchBook. However, to focus on the deals most relevant to my research question, I need to apply additional filters. I begin by collecting all deals from the PitchBook database and then applying the following criteria to narrow the sample to those most relevant to my research: both the investors and portfolio companies must have their headquarters in the U.S., with available office addresses. The deal dates must fall between January 2017 and January 2023, and the founding years of both investors and portfolio companies must be available. Additionally, the PitchBook variable "Investor Status" must be listed as "active." The "Primary Investor Type" cannot be "corporation," "PE-backed company," "VC-backed company," or "other." These criteria yield approximately 150,000 deals. For each of these deals, I collect cell phone signals around the associated investor and portfolio company buildings from Jan 2018 to Jan 2023, resulting in 85 billion observations of cell phone signals. To transform these signals into meaningful meeting frequency data and conduct the deal-by-month-level analysis, I further narrow the focus to deals with at least one observed meeting during the five-year period, considering only months after the investment date. I also require that the distance between the investor's and portfolio company's offices be at least 200 meters. Finally, I ensure that the PitchBook variable "VC Round" is available for each deal, resulting in a final dataset of about 866,000 deal-by-month observations on active involvement frequency.

2.2. Dependent Variables

2.2.1 Deal Flows

To measure VC deal flow, I use cell phone signal data to determine potential pitch events from startup employees. Unlike public equity markets, where managers can invest in any listed stock, venture capitalists are limited to selecting startups from those willing to pitch and potentially accept funding. While an ideal measure would be a comprehensive list of entrepreneurs who want to pitch to each VC, obtaining such a list isn't feasible. I instead construct a proxy by identifying startup employees and defining pitch events. I define a device as belonging to a startup employee if it appears within 200 meters of the startup office for at least five days in a month, sustained over two months. To further rule out irrelevant frequent visitors like delivery workers, I exclude devices counted as employees at more than five locations. I consider it a pitch event when a startup employee approaches the VC building and remains there for at least 30 minutes.

Using the method described above, I can obtain a list of startups that potentially pitched to each VC in each month. With this list, I create two measures for deal flow. First, I measure the number of startups that pitch to a VC each month. Since VCs can only choose from their available choice set, a larger set provides them with more options, potentially leading to better outcomes. Second, I assess the quality of the pitched startups by measuring the percentage that eventually become unicorns. A higher percentage indicates better-quality deal flow.

In this way, I create a dataset at the VC-by-month level that captures both the quality and quantity of deal flow. To construct my dependent variable, I take the average of these deal flow measures over a period of time after active involvement with portfolio companies.

2.2.2 Online Reviews

To understand how entrepreneurs react to VC active involvement behaviors, I analyze online review data about venture capitalists from VC Guide[5]. VC Guide is a platform where founders submit anonymous reviews of VCs they work with. According to the website, the goal of VC Guide is to help founders navigate the venture world and level the playing field. The review submission form is invite-only to ensure the quality of reviews.

[5] The original website of VC Guide is `https://www.vcguide.co/`, but it has been unavailable since 2023. Internet archive tools like `https://web.archive.org/` can help retrieve information that previously appeared on the site.

Each review asks founders to provide an honest assessment of their experience with a VC, including anecdotes and context to help other founders. The reviews also include sliding-scale statements that ask, "On a scale from 1-10 (1 = strongly disagree; 10 = strongly agree), to what extent do you agree with this statement?" A key aspect relevant to this paper is "Adds Value (Hiring, Fundraising, Selling)," explained as "Investor overall adds value to founders with customer intros, hiring, fundraising, etc."

There are 2,284 reviews with overall ratings, and 866 reviews that contain specific ratings on the "value-adding" aspect. The average overall score is 7.7 with a standard deviation of 3.06, on a scale from 1 to 10. The website was first launched in early 2020 and updates monthly thereafter. I used fuzzy matching by name to merge the data with the PitchBook sample, resulting in 424 VCs that are included in further analysis. Table 1 provides the summary statistics of review ratings.

2.2.3 Future Investment Performance

Finally, to test the hypothesis that more active involvement helps VCs invest in better startups in the future, I use the unicorn rate constructed from the PitchBook dataset to assess investment quality. A unicorn is defined as a private startup with a valuation of over $1 billion in a financing round. The unicorn rate is calculated as the number of invested startups that eventually achieve unicorn status divided by all investments over a given period. While achieving unicorn status is a sign of success, it doesn't necessarily translate to huge profits for VCs in my sample, as I count investments made at any financing stage. A VC could see significant profits if they invest in the early rounds before the startup becomes a unicorn, but it's also possible that a VC invests in a round just before unicorn status is achieved, when the valuation is already high. Additionally, the sample period, from 2018 to 2023, saw rapid growth in unicorn creation. For instance, by the end of 2017, the cumulative number of unicorns among private US venture-backed startups was only 110. However, between 2018 and 2023, more than 800 unicorns were created in North America.

Previous papers have also used IPO or M&A rates as measures of success. In this paper, I focus on the unicorn rate because it typically represents a higher benchmark than IPO or M&A, and achieving unicorn status is more likely to reflect a startup's high innate quality ex-ante. This makes it a more suitable measure for showing that VCs with active involvement tend to attract startups that already have high quality at the time of pitching.

2.3. Instrumental Variable

The instrumental variable (IV) used in this study is a measure of travel ease, represented by the actual traveling population between the VC and the portfolio company buildings in a given month. To ensure that this IV doesn't include visits related to VC activities, I exclude all potential VC and startup employees and further reduce overlap by focusing on the weekend travel population, as VC employees are more likely to visit during weekdays. This approach helps minimize any overlap between the IV and the independent variable, which represents on-site VC involvement typically occurring on weekdays. In the robustness check, I also explore using the traveling population across all days as the IV, and the main results still hold.

The inclusion condition is likely met with the following rationale: when travel is easier, VCs tend to visit portfolio companies more frequently. Due to various exogenous shocks, such as changes in weather conditions, road improvements, or new airline routes, both the number of random passersby and VC meetings may increase or decrease simultaneously. As a result, the IV might positively predict VC active involvement intensity.

In terms of the endogeneity of active involvement, Bernstein et al. (2016) is the first paper to tackle this challenge by using a specific exogenous shock: the introduction of new airline routes that reduced travel time. Their approach is novel and highly effective in various contexts. In my paper, since I can directly quantify VC meeting frequency and leverage the novel cell phone dataset, I propose using traveling passersby as an IV. Given that distances between VCs and portfolio companies can range from a few blocks to thousands of miles, the factors affecting ease of travel may vary significantly. This traveling passersby IV is designed to capture travel ease between any two buildings and can account for shocks in travel ease across both short and long distances. The IV in this paper serves as a supplement to the existing method and is well-suited to my setting.

The summary statistics for the independent variable, instrumental variable, and outcome variables used in the regressions are shown in Table 1 below. Since the regressions are conducted at the deal-by-month level, all observations in the summary statistics are also presented at the deal-by-month level.

3. Stylized Facts about VC Active Involvement

In this section, I use the comprehensive dataset detailed earlier to construct a series of graphs illustrating key aspects of VC active involvement. These figures reveal trends that were previously only mentioned in anecdotes. The graphical analysis has two main purposes: first, to highlight significant patterns in VC active involvement, and second, to serve as a sanity check for the dataset, confirming its consistency and reliability for further analysis. While some figures aren't directly tied to the reputation channel in this paper, they offer additional evidence that helps us understand VC active involvement.

3.1. Stylized Fact 1: VCs visit underperforming portfolio companies more frequently

Figure 1 illustrates the relationship between VC active involvement intensity and corresponding profits across different categories of portfolio companies, categorized by exit multiples or valuation step-ups ranging from less than 1x to more than 10x. One caveat of the figure is that the right and left bars are not derived from the same data source, as it is difficult to obtain VC profit composition from the PitchBook dataset. Nevertheless, to the extent that startups with similar exit multiples or valuation step-ups are comparable, the figure reveals an interesting trend: top VCs[6] derive over 90% of their profits from "home runs," or portfolio companies that yield exit multiples of ten times or greater. However, the high-performing portfolio companies receive less than 5% of VCs' resources in active involvement. In contrast, VCs spend over 70% of their time helping startups that eventually return nothing. To understand this discrepancy between VC active involvement resource allocation and final outcomes, I consider three possible explanations. In the following paragraphs, I explore each explanation and discuss the evidence supporting or contradicting it.

The first explanation is that VCs may not be able to determine which startups will succeed, leading them to spend a roughly equal amount of time on each. Given that there are more failed startups than successful ones, VCs end up dedicating more resources to underperforming companies. However, Figures 2 and 3 offer contradictory evidence. In Figure 2, I compare the active involvement intensity for unicorn startups (those not unicorns at the time of investment but eventually achieving this status) with non-unicorn startups. The results indicate that non-unicorn startups receive twice as many meetings as unicorn

[6] This is the composition for top-performing VCs; for more information, see the "Deal Distribution by Share of Funds" figure in https://www.toptal.com/finance/venture-capital-consultants/venture-capital-portfolio-strategy

startups. Concerns may arise that categorizing startups as unicorns or not might be too coarse. Therefore, in Figure 3, I use two continuous measures—PitchBook's startup exit probability and CB Insights' startup rating—to differentiate between good and bad startups. The 2x2 graphs in Figure 3 reveal that better startups receive fewer meetings per month and per funding round, suggesting that VCs can at least partially assess startup quality and choose to focus their active involvement efforts on struggling startups.

The second explanation is that perhaps it's not that VCs spend more time helping struggling startups but that there's a negative treatment effect: more VC meetings lead to worse startup outcomes. This could happen if active involvement disrupts entrepreneurs. However, two pieces of evidence counter this explanation. First, Bernstein et al. (2016) convincingly documents a positive causal relationship between active involvement and startup performance, indicating that increased active involvement leads to more innovation and a higher likelihood of going public. Second, in Section 5.2, I show that more active involvement leads to better entrepreneur reviews, suggesting that entrepreneurs generally prefer active involvement activities.

Given that the first two explanations are contradicted by evidence, the remaining one seems more convincing: VCs spend more time on struggling portfolio companies simply because those companies need more help. VCs might anticipate ex-ante that these struggling startups may not yield significant returns but are still willing to assist in order to build a reputation for future benefits. Anecdotal evidence suggests that this is a common way for VCs to advertise themselves, and such a reputation is helpful in attracting new startups. For example, Mark Suster, a Partner at Upfront Ventures, says, "I list all of the companies on my blog, and this includes both VC investments and angel ones. I play open book. I've had to have hard conversations with entrepreneurs when things aren't going well. But I think most would tell you that in tough times, I tend to roll up my sleeves rather than head for the door." (Suster (2010)) In Section 5, I show that active involvement helps VCs attract better deal flow and, in turn, achieve better future performance, lending support to this explanation. Overall, this first stylized fact motivates the research question in this paper.

3.2. Stylized Fact 2: The Frequency of Visits Increases When Portfolio Companies Are Closer

Figure 4 depicts the relationship between distance and active involvement intensity. The left panel focuses on deals where the distance is less than 20 kilometers, showing a pronounced sensitivity of active involvement intensity to shorter distances. As the distance increases beyond 20 kilometers, the average active involvement frequency declines rapidly. This negative correlation between distance and active involvement intensity aligns with anecdotal evidence. Additionally, the size of each circle represents the number of observations within each interval. The larger circle sizes within the first 5 kilometers suggest a higher frequency of VC investments in nearby startups, consistent with the "home bias" phenomenon widely documented in the existing literature.

3.3. Stylized Fact 3: Early-Stage Investments Receive More Frequent Visits

Figure 5 explores the relationship between the financing round of a deal and the intensity of VC active involvement. For each deal, I calculate the average frequency of monthly meetings from the deal initiation date to the subsequent financing round. As the financing rounds progress from the angel round through the 6th round, the frequency of meetings gradually decreases. This trend is consistent with the typical progression of early-stage startups. These companies, being less mature with less established business operations, require more frequent meetings for guidance. As portfolio companies advance to later stages, the need for intensive active involvement decreases, leading to a corresponding reduction in the frequency of meetings.

3.4. Stylized Fact 4: Different Investors Have Different Involvement Intensities

Figure 6 illustrates variations in active involvement intensity among different types of investors. As the figure shows, accelerators and incubators engage in the most frequent active involvement activities, averaging about 0.6 meetings per month. This higher level of active involvement aligns with their focus on early-stage startups, which generally require more guidance and support. Other investor types tend to exhibit lower active involvement intensity. Angel investors, VCs, PE (buyout) firms, and corporate venture capital (CVC) entities typically have about 0.4 meetings per month. This intensity is comparable to the survey evidence in Bernstein et al. (2016), where the 300 VC respondents report that the median number of visits per year is 6, which translates to 0.5 meetings per month. Hedge funds show slightly lower on-site involvement. Notably, VCs have the smallest standard deviation among all investor types, reflecting that active involvement is a more consistent industry practice in VC but less common in other sectors. Overall, the figure demonstrates that early-stage investors, such as accelerators and incubators, meet more frequently with startups, while other investor types tend to have fewer meetings with their portfolio companies.

3.5. Stylized Fact 5: Deals with More Co-Investors Have More Total Visits but Less Visits per Investor

Figure 7 illustrates the relationship between the number of investors in a deal and the active involvement intensity of each investor. For deals with only one investor, the investor meets with the portfolio company more than half a month on average. However, as the number of co-investors in a deal increases, each individual investor tends to spend less time helping the portfolio company. Interestingly, although the number of meetings for each investor decreases as the number of investors in a deal increases, the total number of meetings between VCs and the portfolio company rises. For example, deals with one investor might have a total of 0.5 meetings per month, but deals with five investors could have a combined total of 2 meetings per month (0.4 meetings per investor times five investors).

This suggests that while there might be a tendency for individual investors to rely on others' efforts in larger syndicate deals, the overall support that startups receive actually increases with the number of co-investors. This pattern aligns with existing literature suggesting that the problem of free-riding is not as severe in the VC industry, given that a lead investor is often present to effectively mitigate such concerns (Da Rin et al. (2013)).

3.6. Stylized Fact 6: Larger VCs Visit Less Frequently Per Deal

As shown in Figure 8, larger VCs (measured by higher assets under management, more investments, more exits, or a greater number of employees) tend to have fewer meetings with portfolio companies per deal. This finding aligns with discussions on decreasing returns to scale (DRTS) in the VC industry. Studies like Kaplan and Schoar (2005) and Nanda et al. (2020) document this decreasing returns to scale trend. One hypothesis that aligns with this stylized fact is that as VC fund sizes grow, it's increasingly challenging to find enough skilled employees (Kaplan and Schoar (2005) and Bernstein et al. (2016)). This leads each partner to take care of more portfolio companies, reducing the amount of attention given to each deal, which might impact performance.

Overall, the six stylized facts above illustrate some interesting trends in the VC industry that have not been formally documented before. Additionally, the first stylized fact further motivates the research question: VCs help existing portfolio companies to build up a reputation for future benefits. In the next section, I return to the main research question and discuss the endogeneity challenge and identification strategy.

4. Methodology

This study aims to explore how active involvement affects VCs' reputation and future deal flow. One empirical challenge is the endogeneity issue. For instance, there may be a reverse causality story: more reputable VCs might visit less frequently. This is illustrated by Figure 8, where larger VCs, whose brands are already well-known to many founders, may be less eager to build their reputation compared to newly established VCs. To address endogeneity concerns, this study employs an instrumental variable (IV) approach to investigate the causal relationship. The IV used here is the ease of travel from a VC building to a startup building in a given month, measured by the number of passersby who happen to pass through both locations. The intuition behind this approach is that exogenous shocks—such as weather conditions or changes in regional accessibility—that make travel easier lead to more frequent active involvement by VCs.

To explain the logic behind this IV, I begin with a case study in San Francisco in Section 4.1. Next, I provide further intuition on the first stage in Section 4.2. Finally, I outline the regression specifications used in this study in Section 4.3.

4.1. A Case Study in San Francisco

This subsection presents a case study to provide more intuition for the IV. Figures 13 and 14 in Appendix A illustrate the foot traffic of passersby and VC visits in the San Francisco area for July and August 2021, respectively. Portfolio companies are represented by red dots, and VCs by blue dots.

In Figure 13, the green lines show the foot traffic of individuals (excluding potential VC and startup employees) who passed near both a VC and a portfolio company's buildings during the month. The line width is proportional to the number of passersby (normalized), with wider or darker lines indicating a higher volume of foot traffic. These lines are displayed only for VC-portfolio company pairs, consistent with the independent variable measure. Meanwhile, Figure 14 shows the number of meetings between a VC and a portfolio company for the month. The line width here reflects the number of VC meetings, with wider lines indicating more meetings. It's important to note that line widths should be compared within each figure across the two months, not across figures, as the figures use different scales to normalize the line widths.

To gain intuition on the IV, we focus on the travel between downtown San Francisco (upper left corner) and the Palo Alto region (lower right corner), a hub for many venture capital firms. As shown in Figure 13, there was substantial foot traffic between these regions in July, which significantly diminished in August. This pattern is mirrored in Figure 14, with a high volume of VC meetings in July that significantly dropped in August.

Why were there more passersby and VC meetings between Palo Alto and downtown San Francisco in July compared to August? One potential explanation is the forest fire that impacted traffic en route. By examining weather conditions in San Carlos, located midway between San Francisco and Palo Alto, we observe that while July had no abnormal weather conditions, August saw 10 days of extreme weather, likely from forest fires, with smoke mostly affecting weekdays, as shown in Figure 15. Overall, the story behind the case is that exogenous weather shocks made traveling from Palo Alto to downtown San Francisco more difficult in August, which is captured by the IV—fewer passersby crossed between Palo Alto and downtown San Francisco. As travel became more difficult, VCs tended to visit less often as well.

It's important to note that these exogenous shocks in travel ease—whether due to weather, road conditions, or new airline routes—occur at the VC-by-portfolio-company-by-month level and are not absorbed by VC-location-by-month or portfolio-company-location-by-month fixed effects. By including these fixed effects, I can control for local economic shocks while still using the IV to capture exogenous shocks in VC active involvement.

4.2. Descriptive Facts about the First-Stage Regression

To better understand whether the IV holds in the first stage, I start by plotting the raw data of traveling passersby against the VC's active involvement intensity for the same VC-startup pair and month, as shown in Figure 9.

As Figure 9 indicates, there is a strong positive correlation between the number of passersby and the frequency of VC meetings for each deal in each month. In the following regressions, I apply log transformations to both the IV and X for two reasons. First, the raw data suggest that the number of VC meetings is much smaller in magnitude compared to the number of passersby. Log transformations help to reduce this range discrepancy, providing stronger predictive power in the first stage. Second, interpreting the results in terms of sensitivity to active involvement is more meaningful, allowing for statements like, "a 10%

increase in the number of monthly visits results in a given change in outcome variables."

However, the positive correlation between VC meetings and the corresponding number of passersby, as shown in Figure 9, does not necessarily indicate a strong first-stage relationship. This correlation might be driven by the distance between a VC and a startup: when the two buildings are closer, there are more passersby, and VC visits are more frequent because the commute is less time-consuming. If the observed correlation is driven primarily by distance, then the first-stage relationship might be weak, raising concerns about the validity of the IV. This is because, in all regressions, I control for VC-startup pair fixed effects, which fully account for deal-specific variables like distance.

To test whether distance is the key driver of the correlation, I plotted Figure 10 to examine the relationship between the IV and the independent variable after controlling for distance. Specifically, I used a simple OLS regression to regress the IV against distance (along with a constant term), then plotted the residuals on the x-axis. Similarly, I regressed the independent variable against distance (with a constant term) and plotted those residuals on the y-axis. The strong positive correlation in Figure 10 indicates that the IV (log passersby) can still strongly predict the independent variable (log VC meetings) even after controlling for distance.

The fact that the IV can strongly correlate with the independent variable even after controlling for distance seems to indicate a strong first-stage relationship. However, there is an additional concern that this correlation might be driven by monthly variations. For instance, in months with a booming economy, there could be more investment opportunities, leading to more VC meetings. Additionally, this economic upswing might lead to increased travel by passersby. If this monthly variation is the primary factor driving the correlation, the first-stage relationship might still be weak, since the main regression controls for local economic shocks by including VC location by month and startup location by month fixed effects, which would absorb this monthly variation.

To examine whether this concern is valid, I plot Figure 11 to control for both distance and month. Specifically, I show the residual of the IV after regressing it against distance and month (plus a constant term) on the x-axis, and the residual of the independent variable after regressing it against the same variables on the y-axis. The strong positive correlation in this figure indicates that the IV can still predict the independent variable even after controlling for distance and month. These figures suggest that there is likely sufficient *deal-by-month level* variation that isn't fully absorbed by factors like distance or month. This finding supports the validity of using passersby as the IV for active involvement intensity.

I formally test the first stage and report the results in Table 2. The sample corresponds to the main regression in column (1) of Table 7. The coefficient is positive and significant. The t-statistic is 14, and the Kleibergen-Paap Wald F-statistic exceeds 200, suggesting no issue with weak instruments.

4.3. Baseline Specification

Building on this IV, I proceed to run a two-stage least squares (2SLS) regression. The baseline regression is a deal-by-month level regression. The first stage is:

$$Meetings_{ijt} = \alpha_0 + \alpha_1 Passersby_{ijt} + \alpha_{location(i)} \times \alpha_t + \alpha_{location(j)} \times \alpha_t + \alpha_{ij} + \eta_{ijt} \tag{1}$$

where i represents VC firms, j represents portfolio companies, and t represents months. The expressions $location(i)$ and $location(j)$ refer to the cities where VC firm i and portfolio company j are located, respectively. $Meetings$ is the log of (one plus) the monthly visits between VC firm i and portfolio company j in month t. $Passersby$ is the log of (one plus) the number of passersby who happen to pass through both the VC firm i and portfolio company j in month t. α_{ij} denotes the fixed effects for the VC-portfolio company pairs, while $\alpha_{location(i)} \times \alpha_t$ and $\alpha_{location(j)} \times \alpha_t$ represent the city-by-month fixed effects for the VC's and the portfolio company's cities, respectively.

The second-stage regression is:

$$y_{i,t+t_1,t+t_2} = \beta_0 + \beta_1 \widehat{Meetings}_{ijt} + \alpha_{location(i)} \times \alpha_t + \alpha_{location(j)} \times \alpha_t + \alpha_{ij} + \epsilon_{ijt} \tag{2}$$

where $\widehat{Meetings}_{ijt}$ is the fitted value of the active involvement measure from the first-stage regression. $y_{i,t+t_1,t+t_2}$ is the dependent variable, where t stands for the focal month (i.e., the month when the VC visits the portfolio company), and t_1 and t_2 represent a period of months after the involvement. For example, in column (1) of Table 3, I focus on new pitching startups 0-6 months after involvement, meaning t_1 equals 0 and t_2 equals 6. The coefficient of interest, β_1, captures the impact of active involvement on VC future outcomes.

Note that in the second-stage regression, the main outcome variables (online reviews, deal flow, and future investment performance) are originally at the VC-by-month level, while the independent variable and instrumental variable are at the deal-by-month level. Naturally, I could either collapse the outcome variable to the more granular deal-by-month level or aggregate the independent variable and IV to the VC-by-month level. However, the IV is more intuitive at the deal-by-month level, as it captures travel ease specific to a deal in a given month. Thus, I use the deal-by-month level regression as the baseline. In Section 6.2, I also test robustness with a VC-by-month level regression and find similar results.

This specification accounts for the time-invariant differences between VC-portfolio company pairs (e.g., distance) through VC-portfolio company pair fixed effects and controls for local shocks through location-by-month fixed effects. In all regressions, standard errors are clustered at the VC firm level.

5. Results

In this section, I use two-stage least squares (2SLS) regressions to estimate the impact of VC active involvement. Sections 5.1, 5.2, and 5.3 present the main results, demonstrating how active involvement affects VC future deal flow, review ratings, and future investment performance. Section 5.4 presents subsample test results to address further concerns, including tests that exclude multi-company buildings, split the sample into lead and non-lead investors, and examine the sample before COVID.

5.1. Effect of Active Involvement on VC Deal Flow

In this section, I examine how increased active involvement influences future VC deal flow. I measure the size of deal flow by the number of startups pitching to a VC each month (captured when a startup employee stay within 200 meters of the VC building for over 30 minutes) and the quality of deal flow by the proportion of those pitched startups that eventually (by the end of Dec 2023) become unicorns.

First, I assess the size of deal flow, with the results presented in Table 3. The dependent variable is the number of startups (excluding existing portfolio companies) that pitch to the VC over the next 6, 12, 18, and 24 months after the VC helps its portfolio companies. The coefficients are positive and significant across all time periods. Column (1) shows that a 10% increase in the intensity of involvement with all existing portfolio companies leads to 1 more entrepreneurs pitching per month over the next 6 months. Given that an average of 6.45 entrepreneurs pitch per month in my sample, this translates into approximately a 16% increase in the number of pitching entrepreneurs. A larger number of entrepreneurs pitching to a VC generally indicates a stronger deal flow, as it provides the VC with a broader set of investment options. Therefore, the positive coefficients suggest that increased involvement with existing portfolio companies helps the VC attract more new entrepreneurs and expands its choice set.

Next, I focus on deal flow quality in Table 4. In this table, I aim to show that increased involvement with existing portfolio companies helps the VC enhance its reputation and attract better startups to pitch in the future. The ideal measure of deal flow quality would assess the quality of startups *at the time they pitch to the VC*. However, since it is empirically difficult to determine startup quality at the time of pitching, I use an ex-post measure as a proxy. Specifically, the dependent variable is the percentage of pitching startups that eventually (by the end of December 2023) become unicorns. One concern of this ex-post measure is that it could suggest an alternative explanation: the startups may not have been of higher quality when they pitched, but improved ex-post due to the VC's increased nurturing ability. However, this is highly unlikely, as only 1 in 30 startups that pitch to a focal VC actually receive an investment from that VC. The vast majority of startups that pitch to the focal VC end up being funded by other VCs, making the focal VC's nurturing ability largely irrelevant. Therefore, the ex-post quality of startups is a reasonable proxy for deal flow quality.

Column (1) of Table 4 shows a significant positive coefficient, indicating that more active involvement with existing portfolio companies leads to higher-quality entrepreneurs pitching. Specifically, if a VC increases its active involvement intensity with all existing portfolio companies by 10%, then the average unicorn rate of the pitching startups over the next 6 months will be 0.27 percentage points higher (or a 7% increase in the unicorn rate). Overall, Table 4 indicates that as VCs help their portfolio companies more frequently, they build up their reputation and eventually match with higher-quality startups. This positive sorting between reputable VCs and better-quality startups is consistent with Sørensen (2007), who finds that more experienced VCs tend to match with inherently better startups.

In both Table 3 and Table 4, the effect appears to be short-term, as the magnitude of the coefficients decreases over longer time spans. Comparing columns (1) through (4), we observe a clear pattern. In Table 3, which tracks the number of entrepreneurs pitching to VCs, the significant coefficients decline from 10 in the first 6 months (column (1)) to just 2 over a 2-year period (column (4)). In Table 4, which assesses the quality of pitching startups based on their eventual unicorn status, only the first 6 months (column (1)) show a significant effect, while the coefficients in the subsequent columns are insignificant and have diminished magnitudes.

Why is this effect on deal flow short-term, and what is the mechanism behind the results? One potential explanation is the word-of-mouth recommendation channel: portfolio companies that receive help are likely to recommend VCs to other startups. The impact of word-of-mouth recommendations fades over time, as portfolio companies are more likely to recall recent support rather than assistance provided years ago. Abundant anecdotal evidence suggests that word-of-mouth recommendations are common in the VC industry. This usually happens in two ways: first, founders often speak to existing portfolio companies before choosing an investor. As noted by TDK Ventures (TDK Ventures (2024)), "Founders are increasingly turning the table and conducting their own reference checks and diligence on VCs – including on the latter's failed investments." Second, VCs themselves encourage startups to reach out to their portfolio companies. Fred Wilson, co-founder of Union Square Ventures, explained, "Instead of references, I like to give a list of every entrepreneur I've ever worked with and an email address. I tell them, 'Throw a dart at that list and talk to four or five of them randomly'" (Suster (2010)). Regularly helping existing portfolio companies and encouraging new startups to speak with those portfolio companies is a key way for VCs to advertise themselves and attract future deal flow in the industry.

To provide more direct evidence of this word-of-mouth recommendation channel, I test the following hypothesis: the effect of involvement on deal flow should be stronger if a VC helps a portfolio company that is more connected to startups pitching in the future. The intuition behind this test can be illustrated with two scenarios: in scenario 1, due to an exogenous shock, a VC happens to visit a portfolio company in New York, and the VC's deal flow also primarily comes from New York. In scenario 2, due to an exogenous shock, a VC happens to visit a portfolio company in New York, but the VC's deal flow primarily comes from California. All else being equal, we expect a stronger effect in scenario 1, as the portfolio company receiving help is more likely and more capable of talking to future pitching startups.

To test this hypothesis, I run a subsample test in Table 5. For each deal-by-month observation, I focus on the location of the focal portfolio company and the locations of all future startups that pitch to the focal VC after the focal month. Using these locations, I compute the percentage of new startups pitching to the VC that are located in the same state as the focal portfolio company. Based on this percentage, the full sample is divided into two groups. I exclude the middle 20% of observations, categorizing the top 40% into the "Same State" subsample, with results shown in Panel B, and the bottom 40% into the "Different State" subsample, with results shown in Panel C. As mentioned in the previous discussion, we would expect a larger effect in Panel B because the portfolio company receiving help is geographically closer to potential future startups, making it more likely to recommend the VC to future startups. The results support this hypothesis: the coefficients in Panel B are significant and have a magnitude similar to the baseline in Panel A, whereas the coefficients in Panel C are not significant and are smaller in magnitude. To formally test whether the coefficients for the two groups are statistically different, I run a regression with interaction terms (including interactions with fixed effects) and find a statistically significant difference.

In conclusion, this subsample test provides further evidence that portfolio companies receiving help are potentially connected to the VC's future deal flow. Overall, the word-of-mouth recommendation channel likely explains the underlying mechanism of why helping existing portfolio companies enables VCs to attract better deal flow. This is widely documented anecdotally in the industry and is consistent with the evidence presented in Table 5.

5.2. Effect of Active Involvement on Review Ratings

In this section, I explore the effect of active involvement on VC reputation, measured by review ratings from entrepreneurs. The ratings are sourced from "VC Guide," a platform where startup founders anonymously submit their experiences and reviews of VCs and investors they've met and worked with. The review submission process is invite-only to ensure quality. Each review asks founders to provide an honest assessment of their experience with a VC or investor, often including anecdotes and context to help other founders. A key metric relevant to this paper is "Adds Value (Hiring, Fundraising, Selling)," described as "Investor overall adds value to founders with customer intros, hiring, fundraising, etc." There are 2,284 reviews with overall ratings, and 866 reviews that contain specific ratings on the "value-adding" aspect. The average overall score is 7.7, with a standard deviation of 3.06, on a scale from 1 to 10.

The review rating sample includes 403 VCs, representing 17% of all VCs and 43% of total AUM. When comparing the review rating sample with the full sample (as used in Section 5.1 and 5.3), I find that VCs in the review rating sample tend to be larger, having been founded earlier, with more investments and greater AUM. Specifically, the average founded year, total investments, and log AUM ($million) for VCs in the review rating sample are 2009, 246, and 5.97, respectively, compared to 2011, 88, and 5.04 in the full sample. All differences are statistically significant. This difference in VC size is reasonable, as larger VCs have more portfolio companies, increasing their likelihood of receiving reviews online. One concern regarding sample selection is that if larger VCs are more sensitive to reputational effects, the results from the review rating sample might overestimate the average treatment effect. However, this is unlikely because larger VCs typically have established brand recognition, making their reputations less dependent on ongoing involvement.

To begin the analysis, I plot Figure 12 to show the correlation between VC monthly meeting frequency and their online ratings. The positive correlation suggests that VCs who hold more frequent meetings tend to receive higher ratings. However, this correlation does not necessarily imply causality, as there may be a negative selection effect: more reputable

VCs may visit less frequently because they already have a strong brand image in the industry and are less motivated to build their reputations. This negative selection effect is likely pronounced, as evidenced by the stylized fact shown in Figure 8. Therefore, we need to rely on the identification strategy to examine the treatment effect of active involvement on review ratings.

To formally establish causality, I use the 2SLS regression, with the results reported in Table 6. Observations are at the deal-by-month level. The independent variable, log meetings, represents the log of (one plus) the number of meetings between a VC and a portfolio company for a specific deal and month. The dependent variable is the review ratings. The two ratings considered are the "Overall Rating," a general score entrepreneurs give to a VC, and the "Value-Adding Rating," which is specific to the VC's value-adding activities. Both ratings are on a scale from 1 to 10, with 10 indicating the highest rating. The results in Table 6 show significant and positive coefficients. Specifically, if a VC increases meeting frequency with all existing portfolio companies by 10%, the VC's review rating will increase by roughly 0.365 (a 5% increase in rating). These findings suggest that entrepreneurs generally view VCs more favorably when they visit and provide assistance more frequently.

5.3. Effect of Active Involvement on Future VC Performance

In the previous sections, I document that increased VC involvement with existing portfolio companies helps VCs build their reputation and attract better deal flow. With a larger and higher-quality pool of startups to choose from, VCs are expected to achieve better performance on their future investments. In this section, I test this hypothesis by examining the impact of active involvement on future investment outcomes.

The second-stage results of the 2SLS regression are shown in Table 7. Observations are at the deal-by-month level. The independent variable is the log of (one plus) the number of meetings between a VC and a portfolio company in a given month. The dependent variable is the average quality of the VC's new investments within a specified period (6-24 months, or 12-24 months) after the focal month. Quality is measured by the unicorn rate—the proportion of newly invested startups that eventually (by the end of December 2023) become unicorns. In column (1), the coefficient is 0.029, suggesting that a 10% increase in meeting frequency with all existing portfolio companies leads to the VC investing in better-quality startups over the next 6 to 24 months—those startups have a roughly 0.29 percentage point higher chance of becoming unicorns. This is a notable magnitude: given that the average unicorn rate in the summary statistics (Table 1) is approximately 3.8%[7], the coefficient indicates that a 10% increase in meeting frequency with all existing portfolio companies leads to about an 8% increase in the future investment's unicorn rate.

Column (2) also reports significant results, with even larger coefficients for the 12-24 month period. This may suggest that active involvement takes longer to materialize into better investment outcomes. Interestingly, recall that with a 10% increase in meeting frequency, the quality of the choice set in the 0-6 month period after active involvement increases by 0.27 percentage points, as shown in column (1) of Table 4. This magnitude aligns with the improvement in VC future investments observed 6 to 24 months after active involvement, which shows a similar increase of about 0.29 percentage points. This alignment suggests that the enhanced quality of the choice set may be the primary driving force behind the observed improvement in VC future investment outcomes. This result is consistent with Nanda et al. (2020), which suggests that VC deal flow plays a key role in perpetuating VC performance.

Since this section focuses on the indirect benefit of involvement on VCs' future investments, it is natural to also compare this with the direct benefit on portfolio companies. The direct benefit of VC active involvement on portfolio companies has already been documented by Bernstein et al. (2016), which uses the introduction of new airline routes that reduce VCs' travel times to their existing portfolio companies as an exogenous shock. In Appendix B, I test the direct benefit using my data and find a positive and significant effect on the focal portfolio companies, consistent with Bernstein et al. (2016). I also conduct a simple back-of-the-envelope calculation of the magnitude and find that the indirect benefits are just as important as the direct ones.

Overall, the three main results in Section 5.1, 5.2, and 5.3 likely illustrate the following reputation effect of active involvement: by actively helping portfolio companies, VCs build a reputation for adding value, as reflected in higher review ratings. This enhanced reputation helps VCs attract better deal flow, which eventually leads to improved future investment performance.

[7]This average unicorn rate might seem relatively high because unicorn investment in this paper refers to any instance where a VC invests in a round before the startup reaches a $1 billion valuation, which does not necessarily indicate huge success. Additionally, variables in the summary statistics are shown on a deal-by-month level, and the denominator consists of investments over the 6 to 24-month period rather than the VC's entire investment history.

5.4. Subsample Tests

In this section, I run three subsample tests to address potential concerns and show the robustness of the main results. The first concern involves the possibility that some startups might share the same building with others, making it difficult to determine which startup a VC is visiting. To mitigate this concern, I construct a subsample of deals in which startups do not share a building with any other companies listed in PitchBook. The results for this subsample are reported in column (1) of Table 8. The coefficient is positive and significant, with a magnitude very close to the baseline results. This test suggests that the first concern is not a major issue.

A second concern involves an alternative explanation for my results. Given that the IV represents travel ease, one concern is that it's the improved regional access, rather than active involvement, that leads to better performance. This isn't a major concern in this context, because the IV only reflects easier access to one specific building, and it's not obvious why access to a single location would have a large impact on deal flow outcomes. Nevertheless, I still provide a test to address this issue further. I split the sample into two groups: one with deals where the VC is the lead investor and the other with deals where the VC is not the lead investor. The intuition is that if improved regional accessibility were driving the results, there shouldn't be significant differences between the two groups. However, as shown in columns (2) and (3), there are significant differences. In the lead investor group (column (2)), the coefficients are significant and larger in magnitude. In the non-lead investor group (column (3)), the coefficients are no longer significant, supporting the idea that active involvement is the main driving force behind the results.

The third concern involves potential changes in active involvement behavior during the COVID, as many on-site meetings shifted to online platforms. To explore this, I run a subsample analysis focusing on data before COVID (January 2018 to January 2020). The results, shown in column (4), are significant and demonstrate a larger magnitude compared to the baseline, indicating that face-to-face interaction (the primary form of active involvement before COVID-19) might be more effective than online interactions. This is consistent with anecdotal evidence suggesting that VCs strongly prefer on-site meetings over virtual ones. Craig Johnson, Managing Director of Concept2Company Ventures, said[8] he knew many venture capitalists who adhered to the doctrine that if a startup company seeking venture capital is not within a 20-minute drive of the venture firm's offices, it will not be funded. This preference for proximity supports the notion that face-to-face interaction plays a crucial

[8]For more details, see `https://www.nytimes.com/2006/10/22/business/yourmoney/22digi.html`.

role in successful active involvement, aligning with the results in column (4).

6. Robustness Checks

In this section, I provide several robustness checks for the main regression results. First, in Section 6.1, I test whether the main results still hold under different filters and data-construction methods. Then, in Section 6.2, I use an alternative VC-by-month level regression instead of the deal-by-month level regression used in the baseline. Lastly, I test different ranges for the involvement period, with the results shown in Appendix C.

6.1. Alternative Data-Construction Method

To evaluate the robustness of the main regression results, I examine different data-construction methods in this section. The baseline method involves several steps. First, I identify if a device likely belongs to a VC employee. This is defined as a device appearing within 200 meters of a VC building for at least five working days in a month and observed for at least two months. To distinguish VC employees from frequent visitors like delivery workers, I exclude those counted as employees at more than five companies. Second, I define a meeting as an event where a potential VC employee appears within 200 meters of a portfolio company's office building during working hours and stays for at least 30 minutes.

However, there is a concern that the results might be sensitive to the chosen data-construction method. To address this, I test alternative data-construction methods by adjusting one filter at a time and present the results in Table 9. The first row shows the baseline specification, which corresponds to Table 7. The following rows adjust specific filters: reducing the distance from 200 meters to 100 or 50 meters; changing the required number of days in a month from 5 to 10 or 15 days; reducing the observed duration from 2 months to 1 month or increasing it to 3 months; setting the maximum companies per employee from 5 to 1 or 10; and altering the minimum meeting duration from 30 minutes to 10 or 60 minutes. The last row changes the measure to "visits," counting unique VC visits instead of meetings (as one meeting might involve multiple venture capitalists). All other aspects of the regression remain unchanged from the baseline regression.

Table 9 demonstrates that the results are consistently significant and positive across different methods. In terms of magnitude, most alternative methods yield similar results, with the exception of the second row where the magnitude is 10 times larger than the baseline.

A stricter 50-meter distance filter might exclude valid meetings, leading to an overestimation of the effect's magnitude. For example, consider two VC firms: one that doesn't meet at all and another that holds four meetings with a startup in a given month. If the second firm achieves a 4% higher unicorn rate due to these meetings, but only two of the four are recorded because of the stricter criteria, it might seem that just two meetings caused the 4% increase in performance when, in reality, it took four. This misrepresentation from stricter criteria might suggest that VC meetings are having a greater impact than they actually do.

The consistent results in Table 9 indicate that the measurement error does not significantly impact the results, demonstrating the robustness of the analysis. While stricter criteria offer a more reliable measure, they may omit valid meetings; more relaxed criteria capture a broader range of meetings but risk including false positives. The fact that all estimators are consistently positive and significant suggests that measurement error is unlikely to be a major concern. While some data-construction methods might be stricter than the actual data-generating process, others could be more relaxed. Given that these strict and relaxed methods define an upper and lower bound, the true effect likely falls within this range. Therefore, the consistent significance and robustness of the results across different methods imply that the relationship between VC active involvement and investment performance is statistically and economically significant.

6.2. Alternative Regression Models

Since the independent variable and IV are at the deal-by-month level while the outcome variables are at the VC-by-month level, there are two approaches for running the regressions. The baseline approach, as shown in Section 5, involves running the regression at the deal-by-month level. This approach has the advantage of maintaining clear and intuitive IV logic, representing how easy it is to travel from a VC building to a startup building within a specific month associated with a deal. Another approach is to aggregate the independent variable and IV to the VC-by-month level. This specification has a limitation in that the IV becomes less precise, representing the average travel ease from a VC to all its portfolio companies in a given month. Nonetheless, I test the robustness by presenting the VC-by-month level regression results in this section. Specifically, the first-stage regression is:

$$Meetings_{it} = \alpha_0 + \alpha_1 Passersby_{it} + \alpha_i + \alpha_t + \eta_{ij} \tag{3}$$

The second stage regression is:

$$y_{i,t+t_1,t+t_2} = \beta_0 + \beta_1 \widehat{Meetings}_{it} + \alpha_i + \alpha_t + \epsilon_{ij} \tag{4}$$

The results are displayed in Table 10. To ensure an apples-to-apples comparison, the outcome variables and time spans are the same as those used in the baseline regression presented in Table 7. In line with standard firm-by-month panel regression, I include both VC fixed effects and month fixed effects. The coefficients are positive and statistically significant, with magnitudes similar to those in the baseline regression, indicating that if a VC firm increases its average monthly active involvement intensity by 10%, its new investments tend to be of higher quality, with a 0.56 percentage point increase in the probability of eventually becoming unicorns. These results confirm the robustness of the main findings under VC-by-month-level specifications.

7. Conclusion

This paper investigates the reputation effects of VCs' active involvement with their portfolio companies. By analyzing cell phone signals near VC and startup buildings, I develop the first empirical measures for VC active involvement intensity and VC deal flow. I use the actual traveling population near buildings that house VC and startup offices as an instrumental variable for VC active involvement intensity and document three main findings: active involvement improves VC reviews, attracts more and higher-quality entrepreneurs, and enhances VC investment performance. These findings support the story that active involvement helps VCs build their reputation, and the resulting enhanced reputation allows them to select from a broader choice of high-quality startups, eventually leading to better investment performance. Besides identifying the effect of active involvement, I also outline six stylized facts about VC active involvement, providing formal evidence for previously anecdotal trends and offering new insights into the VC industry.

The paper's deeper economic message is that it can be optimal for financial intermediaries to exert costly effort to enhance their reputation, because doing so produces benefits in the future. This idea stems from a large, mostly theoretical literature, including classic papers like Chemmanur and Fulghieri (1994), Gorton and Pennacchi (1995), and Pichler and Wilhelm (2001), as well as more recent works like Hartman-Glaser (2017) and Winton and Yerramilli (2021). However, evidence supporting these theories is scarce, likely due to challenges in measuring intermediaries' involvement and reputation, not to mention challenges in identifying causal relations. This paper takes a step toward addressing these challenges and testing this important class of theories.

The cell phone signal data used in this paper are new to the finance literature. These data could be used to study other important finance topics. For example, active involvement also occurs in bank lending, mutual funds, hedge funds, buyouts, and other asset classes. This paper's data-construction method could be applied in these industries to measure investor monitoring and involvement. On a broader scale, the same technique could be used to study face-to-face interactions in various settings. For example, Atkin et al. (2022) employ a similar approach to examine knowledge spillovers among workers. This alternative data opens promising avenues for further research into the effects of face-to-face interactions across many contexts.

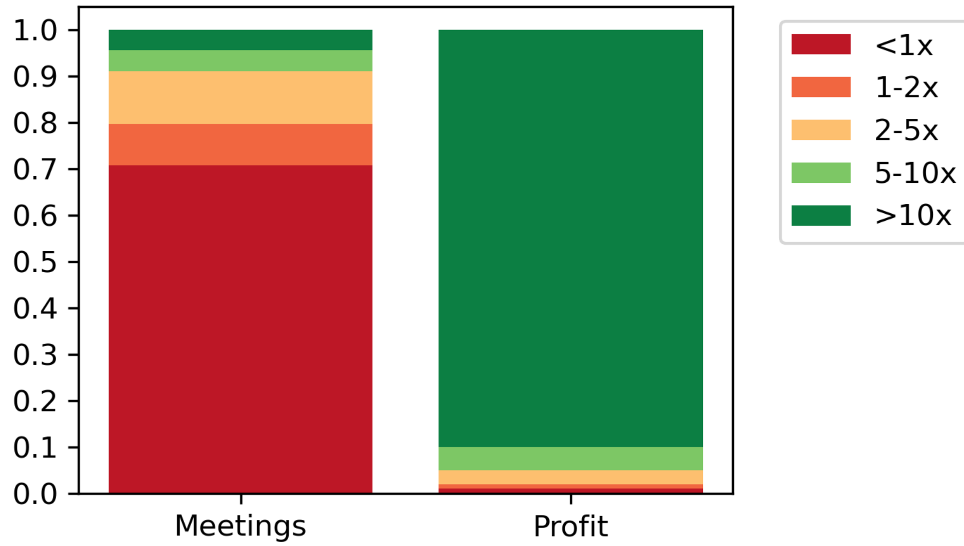

Figure 1. Active involvement intensity and profits for portfolio companies with different exit multiples. The figure delivers a side-by-side comparison of the active involvement intensity across different categories of portfolio companies and the corresponding profits each category generates. The portfolio companies have been classified into five categories according to their exit multiples or valuation step-up: <1x, 1-2x, 2-5x, 5-10x, and >10x. The active involvement measure, represented in the first bar, indicates the percentage of total meetings conducted by VCs and their portfolio companies. The active involvement measure is derived from the main dataset in this paper, while the valuation step-up data is sourced from CB Insight. The second bar showcases the profit shares of each category from successful VC funds that generate returns greater than 5x, with data reported by Horsley Bridge. This profit data is based on an analysis of over 7,000 investments made by funds, in which Horsley Bridge was an investor, spanning the period from 1985 to 2014.

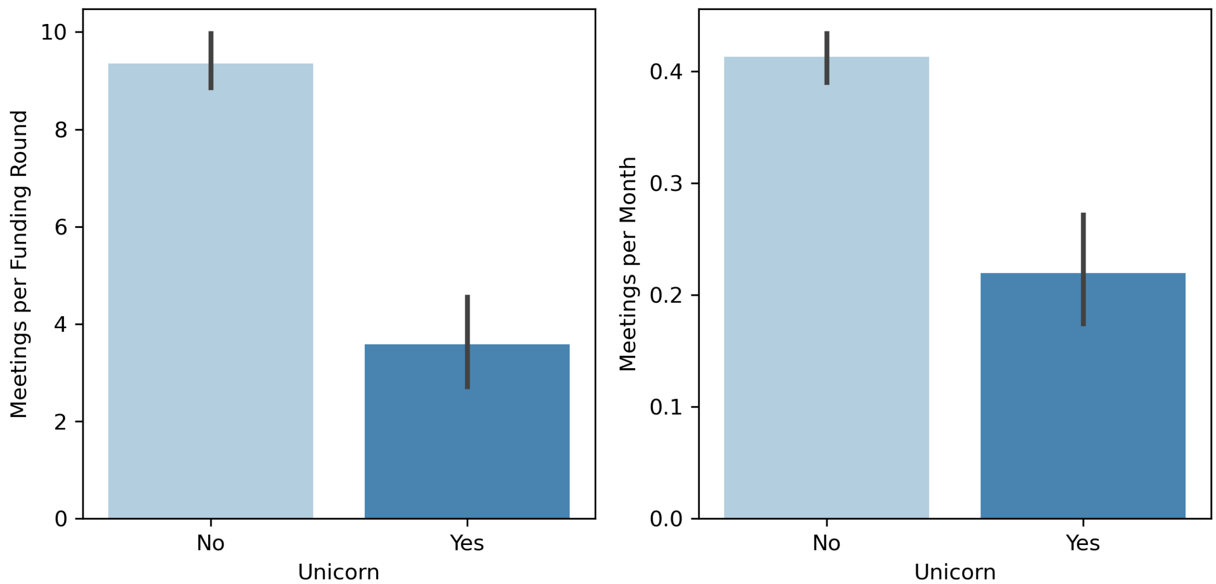

Figure 2. Number of meetings with unicorns vs. non-unicorns. This figure compares the number of meetings VCs hold with unicorn portfolio companies and non-unicorn companies. A unicorn portfolio company is defined as a company that has reached a valuation of at least $1 billion in a financing round as of December 2023. In all the graphs in this section, I calculate the average monthly active involvement frequency from the date of the current deal's investment to the subsequent financing round.

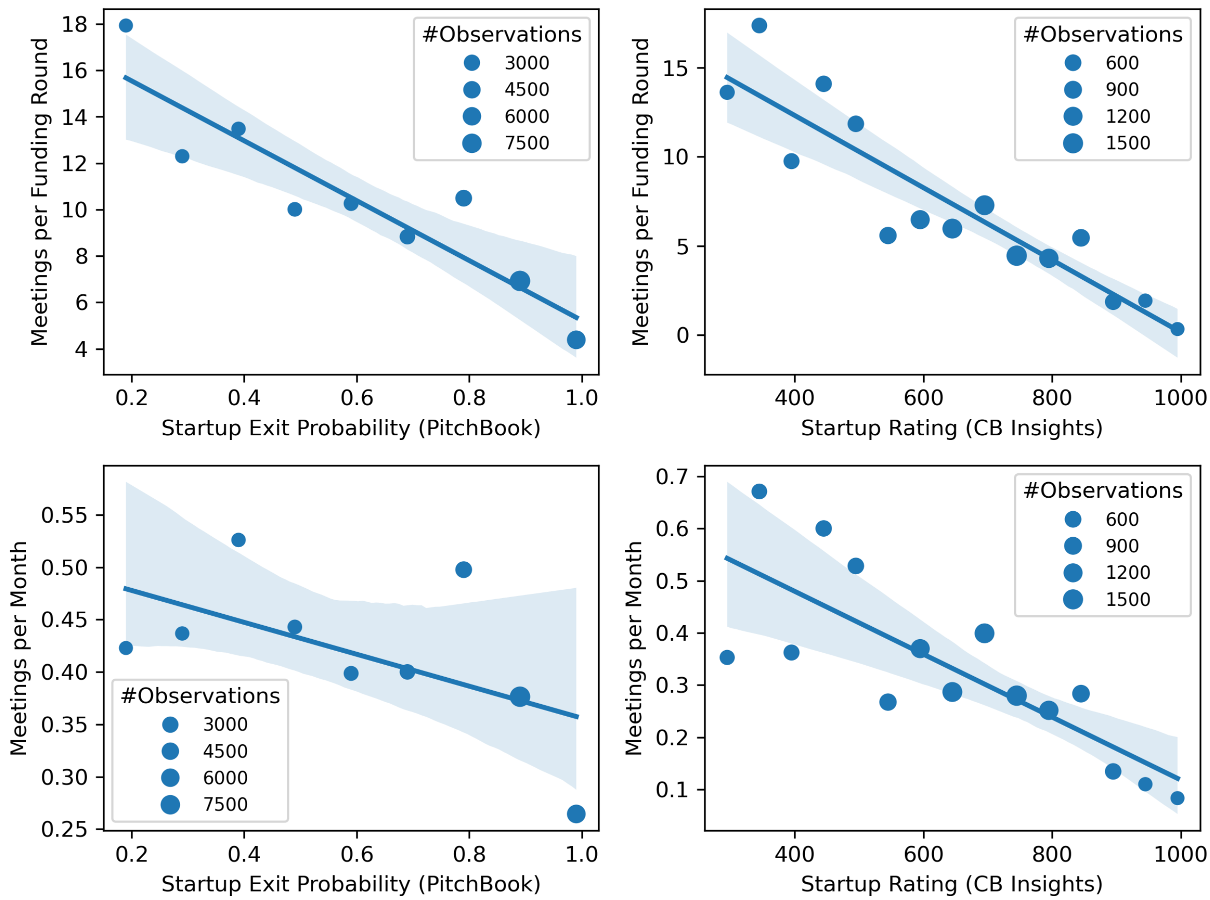

Figure 3. Startup performance and active involvement intensity. The figure illustrates a negative correlation between the performance of portfolio companies and the number of meetings with VCs. The first two subplots show meetings per funding round, while the two subplots in the second row use meetings per month as the x-axis. The first graph in the top row uses the probability of exit to assess portfolio company performance. This metric, taken from PitchBook's "VC Exit Predictor", estimates a startup's chances of achieving a successful exit. Higher exit probabilities suggest superior performance. The second graph in the top row uses the "Mosaic score", a product from CB Insights that evaluates a startup's health and potential for future success. A higher Mosaic score indicates better performance.

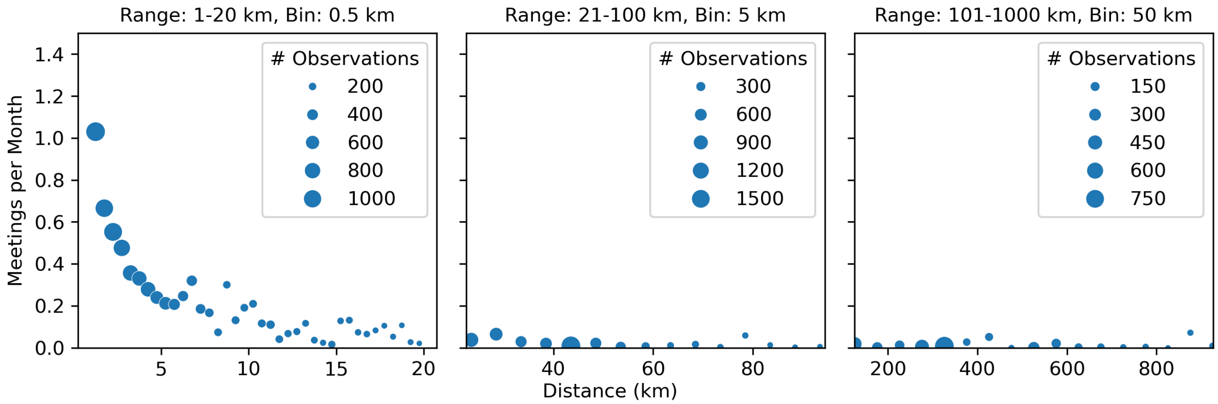

Figure 4. Distance and active involvement intensity. This figure illustrates the correlation between the distance (measured in kilometers) between a VC's office and a portfolio company's office, and the monthly frequency of meetings between the VC and the portfolio company. The figure is constructed at the deal level. The left panel shows deals where the distance is less than 20 km, with each circle representing the average value for each 0.5 km interval. The size of each circle indicates the number of observations in the interval, as depicted in the legend. The middle and right panels represent deals with a distance ranging from 20 to 100 km and from 100 to 1000 km, respectively.

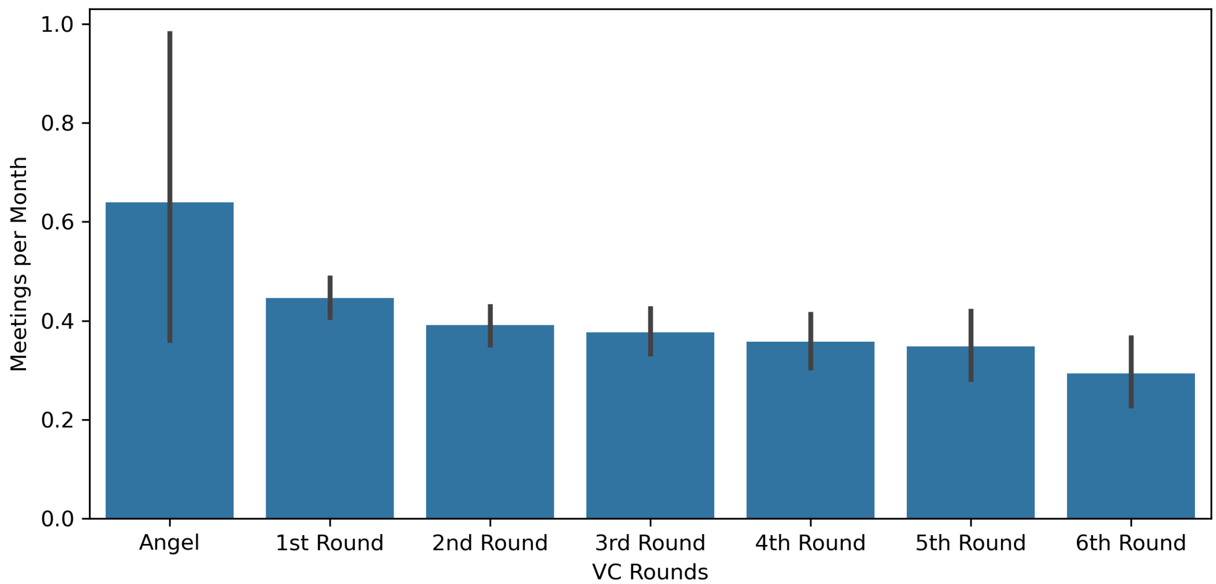

Figure 5. Financing rounds and active involvement intensity. This figure illustrates the relationship between the financing round of the deal and the average frequency of meetings per month between the VC and the portfolio company.

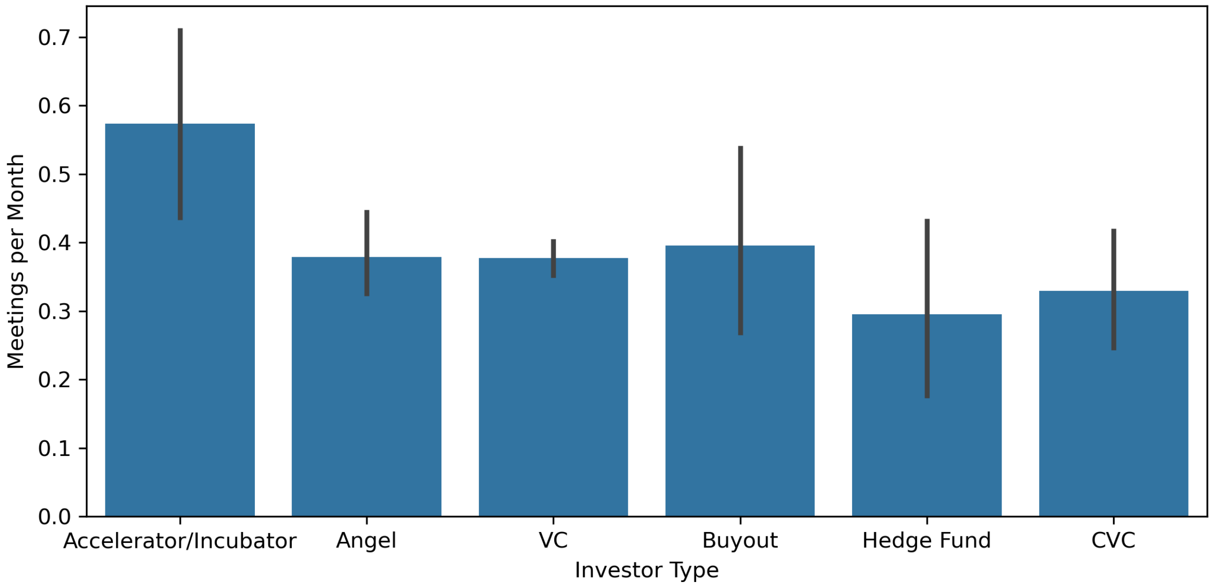

Figure 6. Active involvement intensity by investor type. This figure presents the variation in the average number of monthly meetings between the VC and the portfolio company for different investor types.

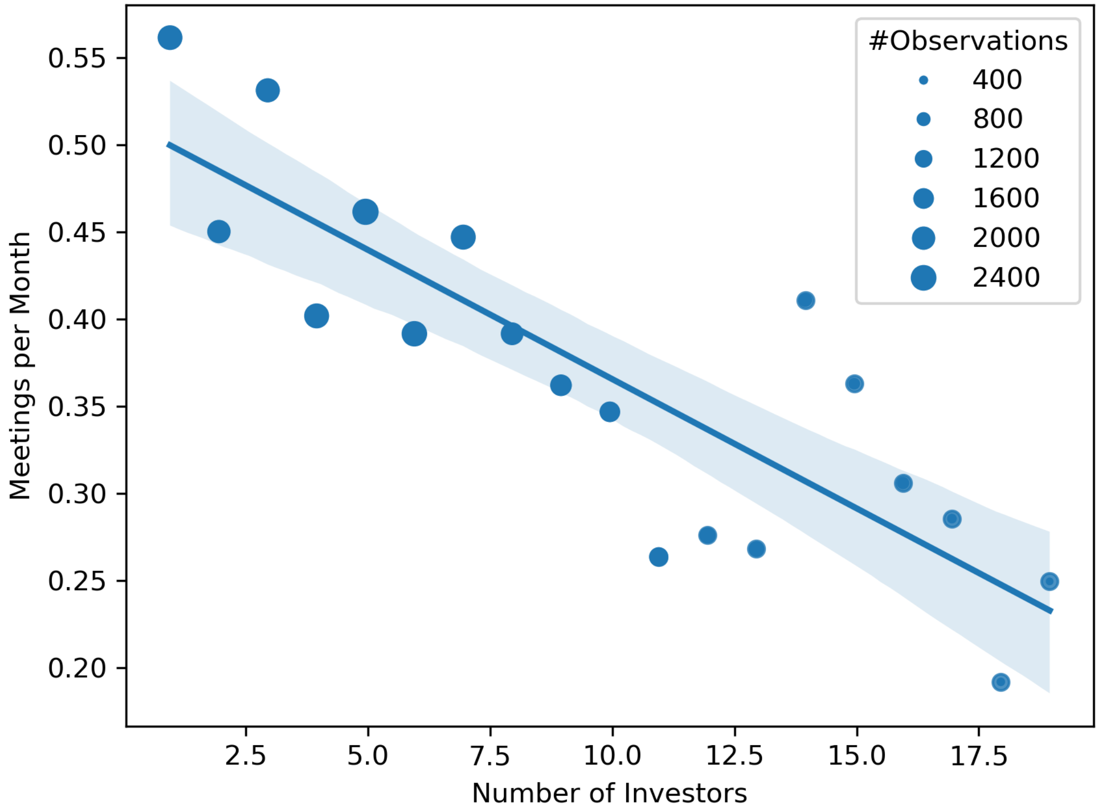

Figure 7. Co-investors and active involvement intensity. This figure illustrates the average monthly meetings between the VC and the portfolio company for deals involving different numbers of co-investors. The size of each circle indicates the number of observations. I include deals with fewer than 20 co-investors, as 20 represents the 95th percentile of the number of co-investors in a deal.

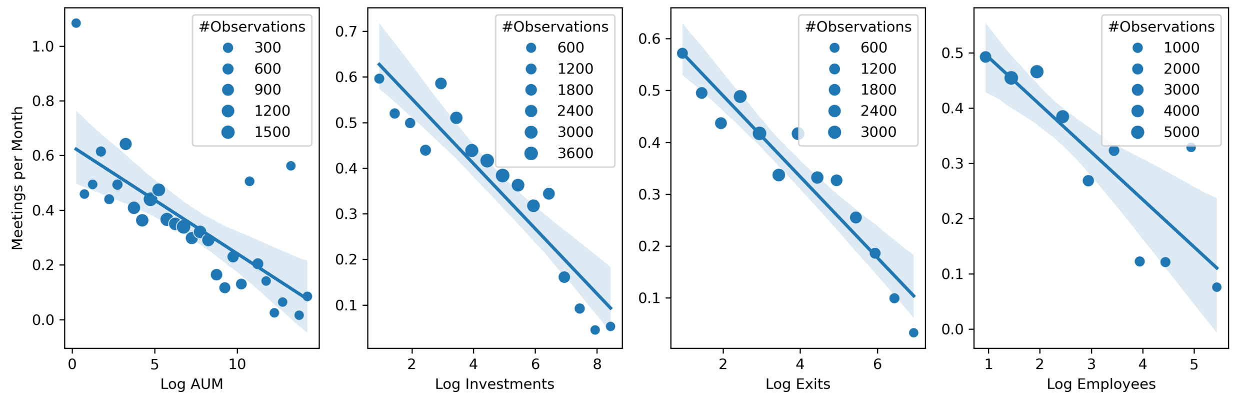

Figure 8. Larger VCs visit less often per deal. The four graphs show the number of monthly meetings per deal for VCs of varying sizes, measured by the log of the PitchBook variables "AUM" (in millions of dollars), "Total Investments," "Total Exits," and "Investment Professional Count" (which refers to the total number of investment professionals, including principals, partners, directors, and associates, but excludes non-investment roles like accountants and marketing directors). I use the most recent values available in PitchBook for these measures, which remain constant across different deal dates. In all graphs, I include deals within the 99th percentile for the x-axis values.

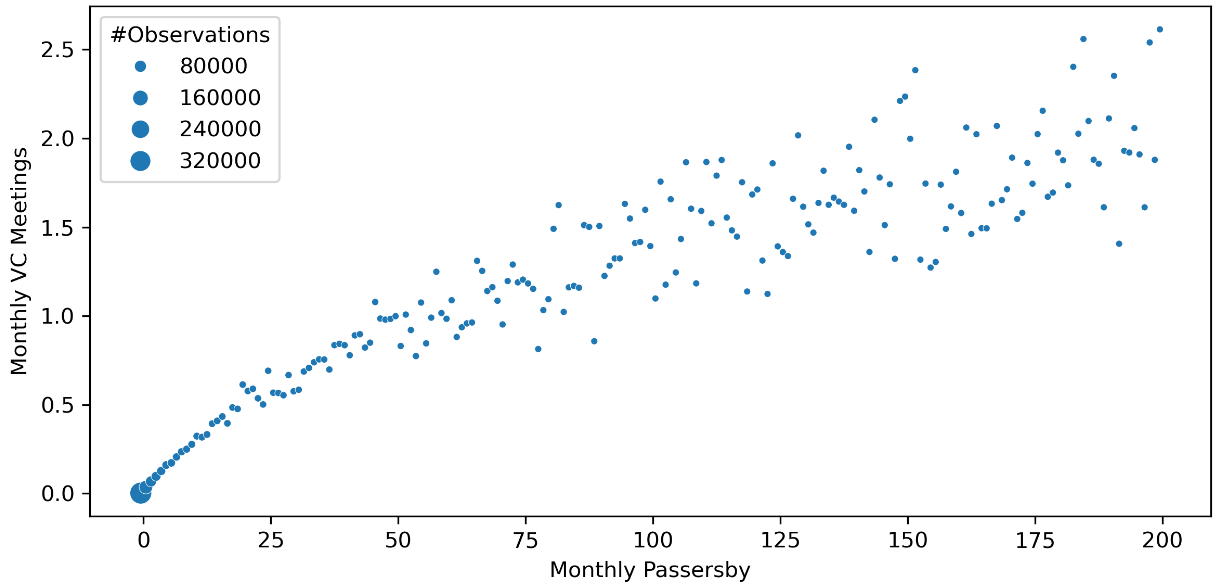

Figure 9. The relationship between the number of passersby and VC meetings. The graph displays the number of passersby against the number of VC meetings for each deal in each month after the investment date. This is a binned scatter plot, where the size of the points reflects the number of observations in each bin.

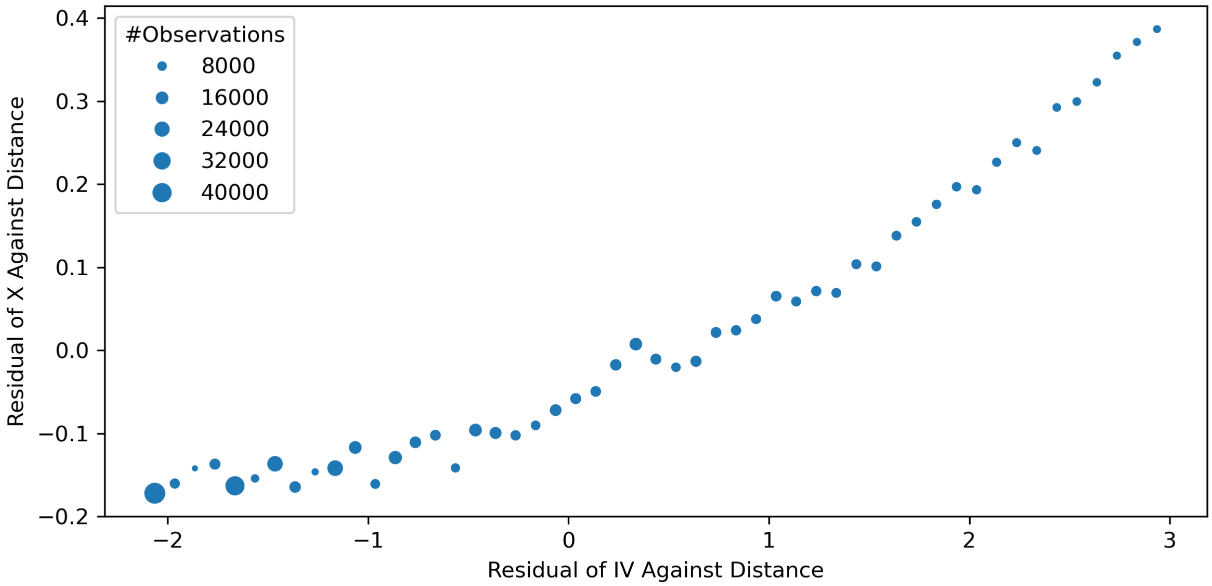

Figure 10. Relationship between IV and X after controlling for distance. The graph represents the log of the number of passersby (IV) and the log of the number of VC meetings (X) for each deal in each month, after controlling for distance. The x-axis shows the residuals from a simple OLS regression of the IV against distance and a constant term. Similarly, the y-axis depicts residuals from regressing the independent variable against distance and a constant term.

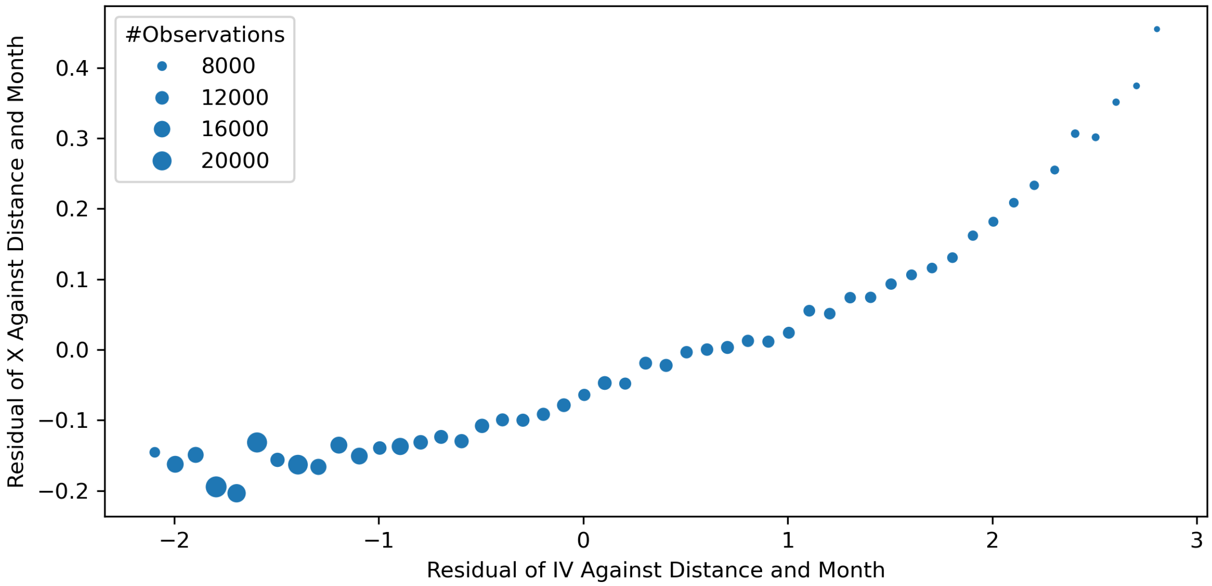

Figure 11. Relationship between IV and X after controlling for distance and month. The graph represents the log of the number of passersby (IV) and the log of the number of VC meetings (X) for each deal in each month, after controlling for distance and month. The x-axis shows the residuals from a simple OLS regression of the IV against distance, month, and a constant term. Similarly, the y-axis depicts residuals from regressing the independent variable against distance, month, and a constant term.

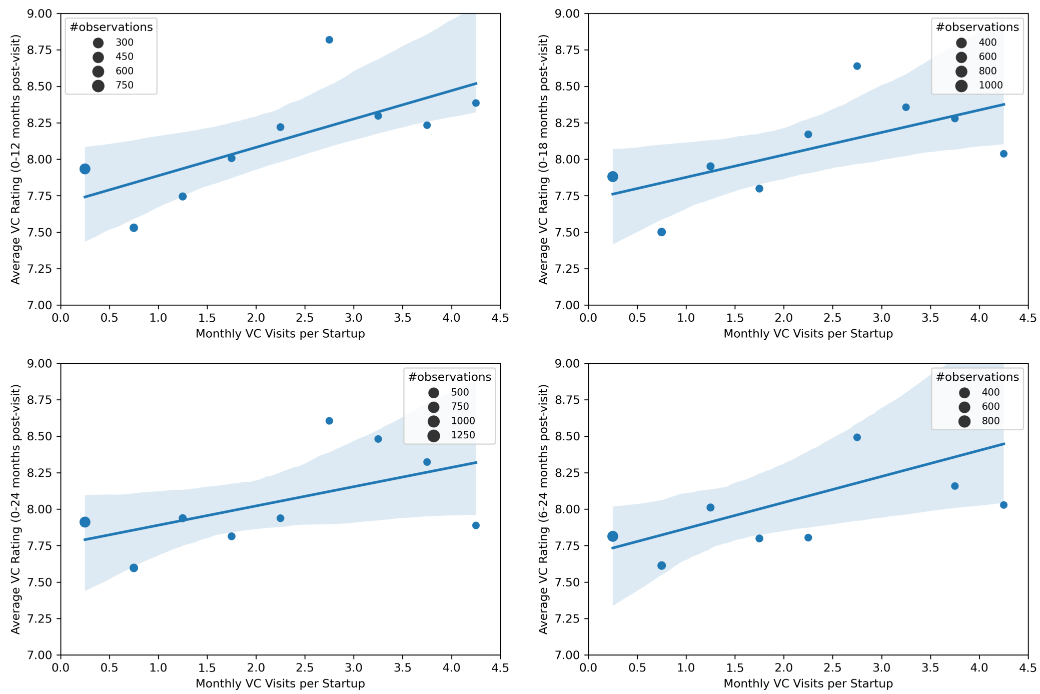

Figure 12. Correlation between VC active involvement and review ratings. The graph shows the correlation between VC active involvement and review ratings. The x-axis represents the number of VC meetings per month, while the y-axis indicates the average overall review ratings for a VC, measured over a specified time span after VC meetings. Each of the four graphs represents a different time span. The review rating's month is based on when the review is posted, typically reflecting the VC's prior involvement with the startup.

Table 1
Summary Statistics

This table presents the summary statistics for the main variables used in the regression analysis, all at the deal-by-month level. In Panel A, the independent variable, *Meetings*, refers to the number of meetings between a VC and a portfolio company for a given deal in a month. In Panel B, the instrumental variable, *Passersby*, indicates the number of unique individuals (excluding potential VC and startup employees) who pass near both the VC's and the portfolio company's buildings in a month. Both variables are transformed into logarithmic terms using log(1+x) for the regression analysis. Panel C includes three groups of outcome variables. First, *Unicorn (6-24)* and *Unicorn (12-24)* represent the unicorn rate for startups newly invested in by the focal VC within the 6 to 24 months and 12 to 24 months, respectively, following the focal month of involvement. The unicorn rate is defined as the percentage of newly invested companies that were valued at less than $1 billion at the time of investment but later reached a valuation of $1 billion or more in a subsequent funding round. These variables are used in Section 5.3 to assess future investment performance. Secondly, *Pitched Startups (0-6)* represents the number of startups (excluding portfolio companies) that pitch to the focal VC within the 6 months following the month of involvement. *Quality of Pitched Startups (0-6)* refers to the unicorn rate of these startups. The variables *Number of Pitched Startups* and *Quality of Pitched Startups* for other periods, such as 0-12, 0-18, and 0-24 months, are defined similarly, with the numbers in parentheses indicating the post-involvement time span. These variables are used in Section 5.1 to evaluate the quantity and quality of the VC's future deal flow. Lastly, *Overall Rating (6-24)*, *Overall Rating (12-24)*, *Adds Value (6-24)*, and *Adds Value (12-24)* represent the review ratings a VC receives over the next 6 to 24 months or 12 to 24 months, respectively, following the focal month of involvement. These ratings, collected from entrepreneurs on the VC Guide website, indicate the VC's reputation among entrepreneurs, with *Overall Rating* capturing the general impression of the VC and *Adds Value* reflecting the VC's perceived ability to add value to portfolio companies. These variables are analyzed in Section 5.2 to measure the VC's reputation.

Variables	Obs	Mean	Std
Panel A. Independent Variable			
Meetings	866,134	0.447	2.443
Log Meetings	866,134	0.109	0.470
Panel B. Instrumental Variable			
Passersby	866,003	44.308	166.321
Log Passersby	866,003	1.702	1.873
Panel C. Outcome Variables			
Unicorn (6-24)	528,815	0.038	0.083
Unicorn (12-24)	405,543	0.038	0.088
Number of Pitched Startups (0-6)	291,465	6.450	9.136
Number of Pitched Startups (0-12)	291,465	6.160	7.512
Number of Pitched Startups (0-18)	291,465	6.035	6.748
Number of Pitched Startups (0-24)	291,465	5.939	6.320
Quality of Pitched Startups (0-6)	266,814	0.038	0.066
Quality of Pitched Startups (0-12)	274,159	0.037	0.056
Quality of Pitched Startups (0-18)	275,794	0.037	0.053
Quality of Pitched Startups (0-24)	276,208	0.037	0.052
Overall Rating (6-24)	92,459	7.921	2.303
Overall Rating (12-24)	60,862	7.930	2.344
Adds Value (6-24)	73,992	7.810	2.529
Adds Value (12-24)	48,741	7.795	2.574

Table 2
First-Stage Results

This table presents the first-stage results of the 2SLS regression. The sample corresponds to the main regression in column (1) of Table 7. Observations are at the deal-by-month level. In the first stage, the independent variable is "Log Passersby," representing the log of (one plus) the number of individuals (excluding potential VC and startup employees) who happen to pass near both the VC and the portfolio company buildings in the focal month. The dependent variable is "Log Meetings," representing the log of (one plus) the number of meetings between the VC and the portfolio company in the focal month. The fixed effects used are identical to those in the second-stage regression. Standard errors are clustered by VC and are shown in parentheses. The Kleibergen-Paap Wald F-statistics are reported. Asterisks *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Log Meetings
Log Passersby	0.043***
	(0.003)
Observations	514,104
Pair FE	Yes
Startup by Month FE	Yes
VC by Month FE	Yes
Kleibergen-Paap rk Wald F-stat	203.257

Table 3
Effect of Active Involvement on VC Deal Flow Size

This table presents the second-stage results of the 2SLS regressions, examining the effect of active involvement on VC future deal flow size. The observations are at the deal-by-month level. The independent variable represents the log of (one plus) the number of meetings between a VC and a portfolio company in a given month. The dependent variable is the average number of startups (excluding existing portfolio companies) that pitch to the VC per month within a specified period (0-6 months, 0-12 months, 0-18 months, or 0-24 months) after the focal meeting month. The Kleibergen-Paap Wald F-statistics for the first-stage are reported. Standard errors are clustered by VC firm and are shown in parentheses. Asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Size (0-6)	(2) Size (0-12)	(3) Size (0-18)	(4) Size (0-24)
Log Meetings	10.205***	5.426***	3.791***	2.629***
	(1.867)	(1.236)	(0.893)	(0.725)
Observations	278,366	278,366	278,366	278,366
Pair FE	Yes	Yes	Yes	Yes
Startup by Month FE	Yes	Yes	Yes	Yes
VC by Month FE	Yes	Yes	Yes	Yes
Kleibergen-Paap rk Wald F-stat	105.897	105.897	105.897	105.897

Table 4
Effect of Active Involvement on VC Deal Flow Quality

This table presents the second-stage results of the 2SLS regressions examining the effect of active involvement on VC future deal flow quality. Observations are at the deal-by-month level. The independent variable represents the log of (one plus) the number of meetings between a VC and a portfolio company in a given month. The dependent variable is the average quality of the new entrepreneurs who pitch to the VC within a specified period (0-6 months, 0-12 months, 0-18 months, or 0-24 months) after the focal meeting month, measured by the proportion of those startups that eventually become unicorns. The first-stage Kleibergen-Paap Wald F-statistics are reported. Standard errors are clustered by VC firm and are shown in parentheses. Asterisks *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Quality (0-6)	(2) Quality (0-12)	(3) Quality (0-18)	(4) Quality (0-24)
Log Meetings	0.027**	0.015	0.013	0.012
	(0.013)	(0.011)	(0.010)	(0.010)
Observations	255,639	262,292	263,681	264,022
Pair FE	Yes	Yes	Yes	Yes
Startup by Month FE	Yes	Yes	Yes	Yes
VC by Month FE	Yes	Yes	Yes	Yes
Kleibergen-Paap rk Wald F-stat	108.224	110.515	111.588	112.100

Table 5
Heterogeneous Effect of Active Involvement on VC Deal Flow

This table presents the heterogeneous treatment effect of active involvement on deal flow. Observations are at the deal-by-month level, and the coefficients represent the second-stage results of the 2SLS regressions. The independent variable represents the log of (one plus) the number of meetings between a VC and a portfolio company in a given month. The dependent variable is the average number of startups (excluding existing portfolio companies) that pitch to the VC per month within specified periods (0-6 months, 0-12 months, 0-18 months, or 0-24 months) after the focal meeting month. All regressions include "VC-Startup Pair" Fixed Effects, "VC City by Month" Fixed Effects, and "Startup City by Month" Fixed Effects. Standard errors are clustered by VC firm and are reported in parentheses. Asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Panel A presents the baseline results using the full sample, identical to Table 3. Panels B and C use two subsamples. To create these subsamples, I calculate the percentage of new startups pitching to the VC that are located in the same state as the focal portfolio company, based on the list of new startups pitching to the VC in the future. Observations are sorted based on this percentage, with the middle 20% of samples excluded. Observations in the top 40% are categorized into the "Same State" subsample, with results shown in Panel B, while observations in the bottom 40% are categorized into the "Different State" subsample, with results shown in Panel C. Lastly, the difference between the two subsample coefficients is formally tested using a regression with interaction terms.

Dependent Variable	Size (0 to 6)	Size (0 to 12)	Size (0 to 18)	Size (0 to 24)
Panel A. Full Sample				
Log Meetings	10.21***	5.426***	3.791***	2.629***
	(1.867)	(1.236)	(0.893)	(0.725)
Observations	278,366	278,366	278,366	278,366
Panel B. 'Same State' Subsample				
Log Meetings	10.18***	4.540***	2.627**	1.834**
	(2.373)	(1.459)	(1.094)	(0.922)
Observations	109,862	109,862	109,862	109,862
Panel C. 'Different State' Subsample				
Log Meetings	3.289	-1.002	-1.075	-1.429
	(2.686)	(1.950)	(1.366)	(1.337)
Observations	108,052	108,052	108,052	108,052
Difference (Panel B - Panel C)	6.896*	5.542**	3.702**	3.263**
	(3.594)	(2.429)	(1.746)	(1.617)

Table 6
Effect of Active Involvement on VC Reputation

The table presents the second-stage results of the 2SLS regressions analyzing the impact of active involvement on review ratings. Observations are at the deal-by-month level. The independent variable, log meetings, represents the log of (one plus) the number of meetings between a VC and a portfolio company for a specific deal and month. The dependent variable is the review rating, calculated as the average review rating from 6 to 24 months after the focal meeting month (with robustness tests using alternative time spans). "Overall Rating" refers to the entrepreneurs' average rating across all aspects, while "Value-Adding Rating" refers to the entrepreneur's rating on how "Investor overall adds value to founders with customer intros, hiring, fundraising, etc." The first-stage Kleibergen-Paap Wald F-statistics are reported. Standard errors are clustered by VC firm and are shown in parentheses. Asterisks *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Overall Rating (6-24)	(2) Value-Adding Rating (6-24)
Log Meetings	3.652**	3.535*
	(1.612)	(1.981)
Observations	89,460	71,553
Pair FE	Yes	Yes
Startup by Month FE	Yes	Yes
VC by Month FE	Yes	Yes
Kleibergen-Paap rk Wald F-stat	41.954	33.605

Table 7

Effect of Active Involvement on Future VC Investment Performance

This table presents the second-stage results of the 2SLS regressions that examine the effect of active involvement on VC future investment performance. Observations are at the deal-by-month level. The independent variable is the log of (one plus) the number of meetings between a VC and a portfolio company in a given month. The dependent variable is the average quality of the VC's new investments within a specified period (6-24 months, or 12-24 months) after the focal month. Quality is measured by the unicorn rate—the proportion of newly invested startups that eventually (by the end of December 2023) become unicorns. The Kleibergen-Paap Wald F-statistics for the first stage are reported. Standard errors are clustered by VC firm and are shown in parentheses. Asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Unicorn (6-24)	(2) Unicorn (12-24)
Log Meetings	0.029**	0.049**
	(0.014)	(0.020)
Observations	514,104	393,333
Pair FE	Yes	Yes
Startup by Month FE	Yes	Yes
VC by Month FE	Yes	Yes
Kleibergen-Paap rk Wald F-stat	203.257	239.596

Table 8
Subsample Tests

This table presents subsample tests of the main results. The baseline result from the full sample is shown in Table 7, column (1) (the dependent variable is the unicorn rate of the VC's new investments, measured over a time span from 6 to 24 months after the focal month). The subsample results differ from the baseline regression only in terms of sample selection. Column (1) includes only portfolio companies that do not share the same building with any other companies listed in PitchBook. Columns (2) and (3) further divide this sample into deals with lead investors and deals with non-lead investors. Column (4) uses only pre-COVID data, covering the period from January 2018 to January 2020. The Kleibergen-Paap Wald F-statistics for the first stage are reported. Standard errors are clustered by VC firm and are shown in parentheses. Asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Unicorn (6-24)	(2) Unicorn (6-24)	(3) Unicorn (6-24)	(4) Unicorn (6-24)
Log Meetings	0.028*	0.065**	0.020	0.055**
	(0.016)	(0.030)	(0.019)	(0.022)
Observations	164,949	34,614	122,778	146,408
Pair FE	Yes	Yes	Yes	Yes
Startup by Month FE	Yes	Yes	Yes	Yes
VC by Month FE	Yes	Yes	Yes	Yes
Kleibergen-Paap rk Wald F-stat	100.567	29.443	82.726	121.790

Table 9
Robustness Checks with Alternative Data-Construction Method

This table checks the robustness of the main regression results using different data-cleaning methods. The baseline result is the same as the one shown in Table 7. The baseline data-cleaning method defines an employee's device as one that appears within 200 meters of the VC building for at least 5 working days in a month and is observed for at least 2 months. To distinguish VC employees from frequent visitors like delivery workers, a filter excludes devices counted as employees at more than 5 companies. A meeting is defined as an event where a potential VC employee appears within 200 meters of a portfolio company's office during working hours and stays there for at least 30 minutes. This table modifies each filter of the baseline cleaning method. It adjusts the distance from 200 meters to 100 or 50 meters; the number of days in a month from 5 to 10 or 15 days; the number of months from 2 to 1 or 3; the maximum firms per employee from 5 to 1 or 10; and the minimum duration of a meeting from 30 minutes to 10 or 60 minutes. The last row changes the type to "Visits" to consider the number of unique VC visits instead of the number of meetings. All other aspects of the regression remain exactly the same as in the main regression. All regressions contain VC-startup pair fixed effects, VC location by month fixed effects, and startup location by month fixed effects. The total number of observations across all regressions is 514,104, the same as in the main regression. Kleibergen-Paap Wald F-statistics from the first-stage regression are reported. Standard errors are clustered by VC firm and are indicated in parentheses. The asterisks *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Specification	Coef	Std	F-stat	Distance	Days	Months	Firms	Duration	Type
Baseline	0.0290**	(0.0139)	203.3	200	5	2	5	30	Meetings
1	0.0476**	(0.0232)	133.7	**100**	5	2	5	30	Meetings
2	0.262**	(0.133)	39.81	**50**	5	2	5	30	Meetings
3	0.0487**	(0.0237)	109.8	200	**10**	2	5	30	Meetings
4	0.0749**	(0.0370)	73.99	200	**15**	2	5	30	Meetings
5	0.0248**	(0.0119)	285.5	200	5	**1**	5	30	Meetings
6	0.0340**	(0.0164)	169.5	200	5	**3**	5	30	Meetings
7	0.0809**	(0.0394)	100.8	200	5	2	**1**	30	Meetings
8	0.0217**	(0.0104)	342	200	5	2	**10**	30	Meetings
9	0.0259**	(0.0124)	245.1	200	5	2	5	**10**	Meetings
10	0.0327**	(0.0158)	177.9	200	5	2	5	**60**	Meetings
11	0.0256**	(0.0123)	172.6	200	5	2	5	30	**Visits**

Table 10
VC-by-Month Level Regressions

This table presents the second-stage results of the 2SLS regressions, where the data is aggregated at the VC-by-month level. The outcome variables are the same as in Table 7. The regressions include VC fixed effects and month fixed effects. The Kleibergen-Paap Wald F-statistics for the first stage are reported. Standard errors are clustered by VC firm and are presented in parentheses. Asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Unicorn (6-24)	(2) Unicorn (12-24)
Log Meetings	0.056***	0.067***
	(0.011)	(0.015)
Observations	96,041	77,121
VC FE	Yes	Yes
Month FE	Yes	Yes
Kleibergen-Paap rk Wald F-stat	340.161	288.175

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Appendix

A Case Study in San Francisco

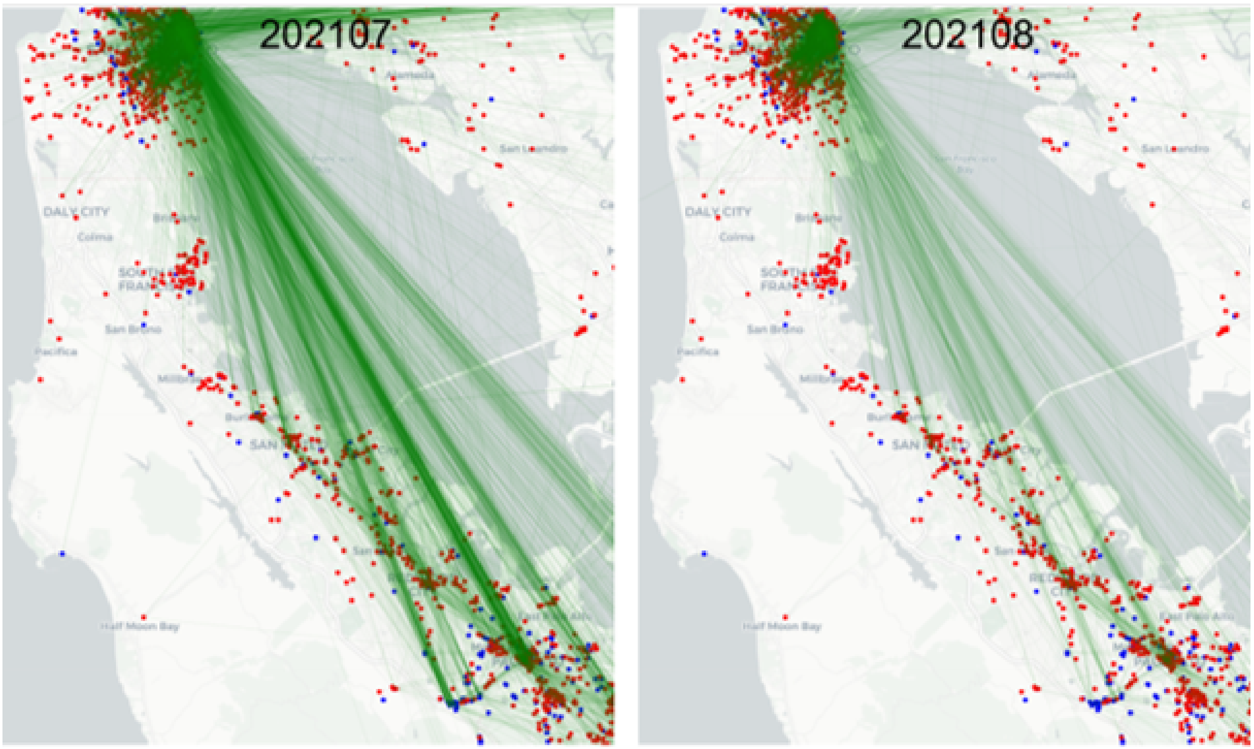

Figure 13. Passerby Traffic Between VC and Portfolio Companies in San Francisco. This figure illustrates the foot traffic of passersby in the San Francisco area for July and August 2021. Portfolio companies are represented by red dots, while VC locations are indicated by blue dots. The green lines, varying in width and darkness, denote the total unique passersby traveling between the VC and startup locations over the weekends of the respective month. The width and darkness of the lines are proportional to the normalized number of passersby, with wider and darker lines indicating a higher volume of travel. These lines are only displayed for active VC-portfolio company pairs, consistent with the independent variable measure. The map's northwestern region represents downtown San Francisco, while the southeastern region denotes Palo Alto, a notable hub for venture capital firms.

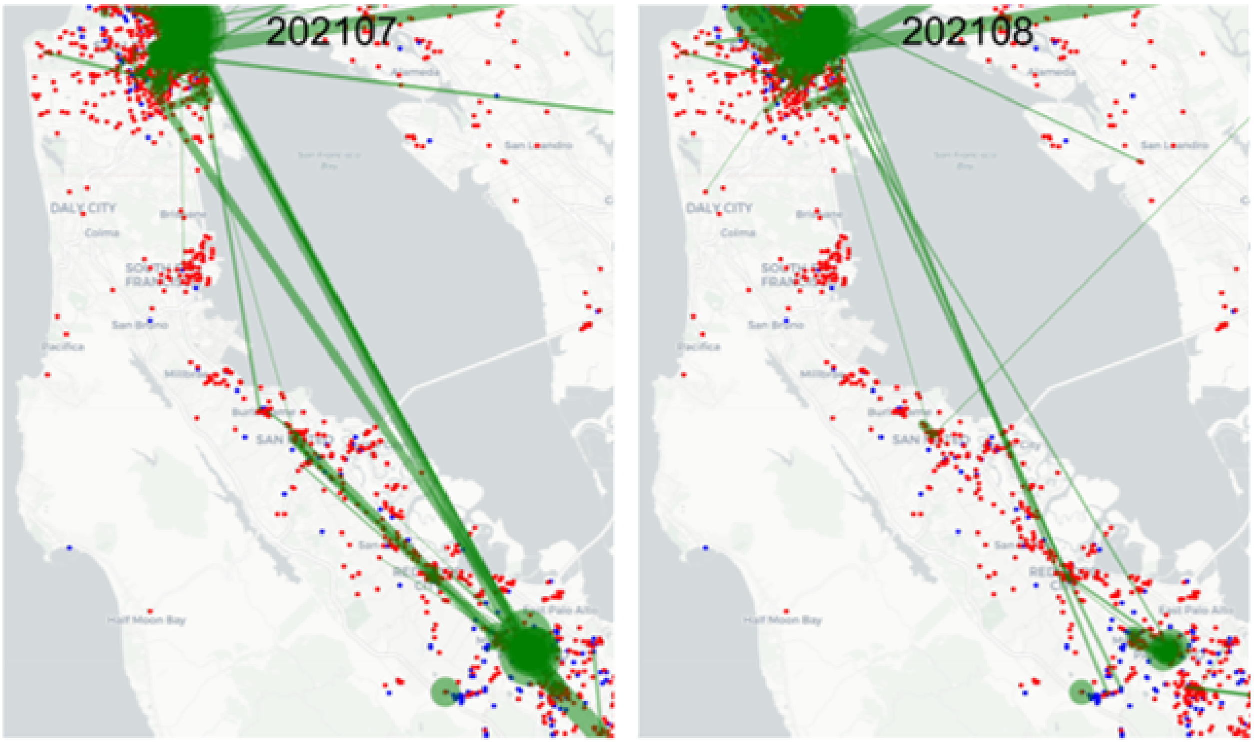

Figure 14. VC Meetings between VC Firms and Portfolio Companies in San Francisco. This figure depicts the frequency of VC meetings in the San Francisco area for July and August 2021. Portfolio companies are denoted by red dots, while VC locations are marked by blue dots. The green lines, varying in width and darkness, represent the total number of weekday meetings between the VC firm and the startup for each respective month. The width and darkness of the lines are proportional to the normalized number of meetings, with wider and darker lines indicating a higher frequency of VC meetings. The map's northwestern region represents downtown San Francisco, while the southeastern region denotes Palo Alto, a hub for venture capital firms.

Figure 15. Weather Conditions at San Carlos in July and August 2021. This figure presents the weather conditions at San Carlos Airport, a location situated en route between downtown San Francisco and Palo Alto, for July and August 2021. The gray bars represent the hours smoke was reported. Data source: https://weatherspark.com/.

B Direct Benefit of Active Involvement

In Section 5.3, I document that increased VC involvement helps VCs invest in better startups in the future. It is natural to compare this indirect benefit with the direct benefit to portfolio companies. The direct benefit of VC active involvement on portfolio companies has already been documented by Bernstein et al. (2016). Here, I test the direct benefit using my dataset, and the results are shown in Table 11. The results show that if VCs increase their monthly meeting frequency with a portfolio company by 10%, the unicorn rate of the focal portfolio company increases by 0.39 percentage points, representing a 10% increase relative to the mean.

Table 11
Direct Benefit of Active Involvement

This table presents the second-stage results of the 2SLS regressions that analyze the direct benefit of active involvement on the focal portfolio company. The independent variable is the log of (one plus) the number of meetings between a VC and the portfolio company in a given month. The dependent variable is a binary indicator equal to one if the focal portfolio company eventually becomes a unicorn by the end of December 2023. The Kleibergen-Paap Wald F-statistics for the first stage are reported. Standard errors, clustered by VC firm, are shown in parentheses. Asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Unicorn	(2) Unicorn	(3) Unicorn
Log Meetings	0.039**	0.049***	0.031*
	(0.018)	(0.018)	(0.018)
Observations	866,003	866,003	866,003
VC FE	Yes	Yes	No
Month FE	Yes	No	Yes
Kleibergen-Paap rk Wald F-stat	665.791	609.564	723.141

However, comparing the magnitudes of the indirect and direct benefits is challenging due to a subtle difference in coefficient interpretations. For the indirect benefit (Table 7), the dependent variable is the unicorn rate of all newly invested startups over the next 6–24 months, which is essentially a VC-by-month-level variable. A 10% increase in the independent variable represents a 10% increase in meeting frequency with all existing portfolio companies for the focal month. For the direct benefit (Table 11), the dependent variable is the final outcome of the focal portfolio company—essentially a deal-level variable—and a

10% increase in the independent variable represents a 10% increase in meeting frequency for the focal portfolio company across all months.

To make an apples-to-apples comparison, consider a scenario where a VC increases its meeting frequency with all portfolio companies in one month by 10%. In my sample, each VC has an average of 21 portfolio companies and invests in 5 new startups over the next 6–24 months. Assuming the direct treatment effect is mainly concentrated in the first 6 months after investment, increasing meeting frequency with each portfolio company by 10% in one month leads to a $0.0039 \div 6 = 0.00065$ higher chance of each becoming a unicorn. Therefore, the total direct benefit is $0.00065 \times 21 \times V = 0.0137V$, where V is the average benefit of investing in a unicorn.

For the indirect benefit, a 10% increase in meeting frequency in one month leads to new investments over the next 6–24 months having a 0.29 percentage point higher chance of becoming unicorns. Given that the VC makes about 5 new investments during this period, the total indirect benefit is $0.0029 \times 5 \times V = 0.0145V$.

Comparing the total direct benefit ($0.0137V$) and the total indirect benefit ($0.0145V$), we find that the indirect benefits are very close to the direct benefits in terms of magnitude. However, the calculation above is just a back-of-the-envelope estimate and may be sensitive to assumptions, so it should be interpreted cautiously with potential caveats in mind. Overall, this section shows that increased involvement leads to better performance for focal portfolio companies, consistent with Bernstein et al. (2016), and the indirect benefits are roughly as important as the direct ones.

C. Alternative Involvement Period

Table 12
Robustness Check Using Alternative Involvement Period

This table presents a robustness check for the main results in Table 7. The dependent variable is the unicorn rate of the VC's new investments, measured over a time span from 6 to 24 months (or 12 to 24 months) after the focal month. The key difference in this table is that it only includes months between the current financing date and the next, while in the main regression in Table 7, all months after the deal date are included. The Kleibergen-Paap Wald F-statistics for the first stage are reported. Standard errors are clustered by VC firm and are presented in parentheses. Asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Unicorn (6-24)	(2) Unicorn (12-24)
Log Meetings	0.025**	0.041**
	(0.012)	(0.017)
Observations	305,115	245,619
Pair FE	Yes	Yes
Startup by Month FE	Yes	Yes
VC by Month FE	Yes	Yes
Kleibergen-Paap rk Wald F-stat	148.766	197.708

In the baseline regression, I focus on VC involvement with portfolio companies across all months after the deal date. It's also reasonable to consider only the months between the current deal date and the next financing round. In this section, I test the results presented in Table 12. The regressions are the same as those in Table 7, with the only difference being that here, I focus solely on the months between the current financing date and the next. The results remain significant with a similar magnitude, indicating that the findings are robust to different selections of the involvement period.