How Can Monitoring Benefit Investors? Evidence from 85 Billion Cell Phone Signals

Jack Xiaoyong Fu^{*}

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Abstract

I investigate the impact of monitoring on investors, specifically examining how venture capitalists' (VCs') on-site involvement with portfolio companies affects their subsequent deals. By analyzing 85 billion cell phone signals collected around VC and startup office buildings from 2018 to 2023, I develop a novel measure of VCs' monitoring activities. I show that increased VC monitoring leads to better deals in the future. Specifically, when VCs double the frequency of their monthly meetings with startups, then one year later, they are twice as likely to invest in startups that eventually become unicorns. This improvement is likely due to enhanced VC reputation, evidenced by VCs with more frequent visits subsequently attracting more experienced CEOs for their future investments. Furthermore, this paper leverages the unique dataset to document eight stylized facts about VC monitoring: (1) VCs monitor underperforming portfolio companies more frequently; (2) VC monitoring frequency correlates with proximity; (3) early-stage investments receive more monitoring; (4) accelerators and incubators monitor more frequently than traditional VCs; (5) PEs, CVCs, and VCs show similar monitoring intensity; (6) deals with more co-investors tend to have more total meetings, but fewer meetings per investor; (7) VCs with more employees hold more total, but fewer per-deal, meetings; and (8) larger portfolio companies attract more monitoring.

^{*}Jack Xiaoyong Fu: the Wharton School of the University of Pennsylvania, fxi@wharton.upenn.edu. I am extremely grateful to Sasha Indarte, Luke Taylor and Yao Zeng for their invaluable support and continuous guidance. I would like to thank William Diamond, Vincent Glode, Paul Goldsmith-Pinkham, Daniel Garrett, Itay Goldstein, John Griffin, Marius Guenzel, Gerard Hoberg, Johan Hombert, David Hsu, Alex Imas, Hyeik Kim (discussant), Gregor Matvos, Jean-Marie Meier, Gordon Phillips, Manju Puri, Huan Tang, Neng Wang, and Jonathan Zandberg as well as seminar and conference participants at the Wharton School, Wharton-INSEAD Doctoral Consortium and WEFI PhD workshop for their invaluable comments and suggestions. I am grateful for funding from the Mack Institute and Jacobs Levy Equity Management Center. The Institutional Review Board at the University of Pennsylvania determined that the research meets the eligibility criteria for IRB review exemption authorized by 45 CFR 46.104, category 4.

1. Introduction

In the venture capital (VC) industry, a puzzling phenomenon persists. VCs allocate onethird of their time to monitoring¹ portfolio companies², especially the underperforming ones³. However, a small number of outstanding portfolio companies generate over 90% of the VCs' total profits, despite representing less than 5% of the VCs' monitoring time. In contrast, all underperforming portfolio companies in aggregate contribute to less than 5% of the VCs' total profits, yet they account for more than 90% of the VCs' monitoring time⁴. This imbalance between intensive monitoring and minimal returns raises a natural question: how does monitoring truly benefit investors, and why do VCs invest such significant time and resources into monitoring activities? While prior studies emphasize the role of VCs' monitoring activities in fostering innovation and success among portfolio companies (Bernstein et al. (2016)), how this monitoring process benefits the VCs themselves remains largely unexplored. In this paper, I investigate the impact of monitoring on investors, specifically examining whether increased monitoring enhances VCs' likelihood of investing in higher-quality startups in the future. I aim to address this puzzle by highlighting the indirect benefit that monitoring offers VCs: Increased VC involvement enhances VCs' founder-friendly reputation, positioning them favorably to attract top-tier portfolio companies in future deals.

The challenge in empirically identifying a causal effect of monitoring activities on VCs' subsequent deals is twofold. The first challenge lies in the scarcity of existing datasets. Typically, VCs' on-site involvement with their portfolio companies occurs off the record, making it nearly impossible to capture a comprehensive dataset documenting these monitoring activities. To address this challenge, I propose a novel method to capture VCs' monitoring activities. I analyze a unique dataset containing 85 billion cell phone signals within a 200meter radius around VC and startup office buildings from 2018 to 2023. Utilizing established technology in the telecommunications sector, this dataset contains cell phone location data, accurate to 15 meters, with timestamps, recorded when an app is active or running in the background. While this technology fully complies with legal standards as it operates without disclosing any personally identifiable information, the raw data still enables the identification of potential meetings between VCs and startups.

From this raw data, I construct a measure of monitoring activities in two steps. First, I

¹"Monitoring", in this paper, is adopted from the general VC terminology as used by Bernstein et al. (2016) and refers to VC involvement and value-adding services to portfolio companies.

 $^{^{2}}$ VCs report that they spend an average of 18 hours per week assisting portfolio companies in the survey of 885 VCs by Gompers et al. (2020).

³Figure 1 and 2 show that VCs spend more time in meetings with worse portfolio companies.

⁴This discrepancy is highlighted in Figure 3.

determine if a device is likely to belong to a VC employee. I define an employee's device as one that appears within 100 meters of the VC building for at least 15 working days in a month. Second, I define a meeting as an event where a potential VC employee appears within 100 meters of an associated 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. Furthermore, robustness checks utilize alternative filters, varying working days, distance, and stay duration for validation. To address the potential concern of tall buildings housing several companies, I further construct a subsample where each VC and startup are the only companies in their respective buildings, serving as robustness checks. Overall, I gathered cell phone signals for more than 10,000 investors (including VCs, PEs, CVCs, accelerators, incubators, and angel investors) and more than 30,000 associated portfolio companies' office buildings from 2018 to 2023, and I recover the monthly meeting patterns for 150,000 active deals, which represents over 95% of active deals recorded in PitchBook. This newly constructed dataset effectively addresses the first empirical challenge.

The second empirical challenge arises from the endogeneity of monitoring activities. Omitted variables, such as a VC's knowledge or expertise, could influence both the frequency of monitoring activities and the subsequent performance of deals. While existing literature, such as Bernstein et al. (2016), has tackled this challenge by leveraging the introduction of new airline routes as exogenous variation in VC involvement, applying this identification strategy to my research would not be suitable due to the comprehensive scope of my dataset. The distances between VCs and portfolio companies can now range from a few blocks to thousands of miles. The determinants of ease of travel vary considerably based on these distances, influenced by daily weather changes, road condition improvements, or the introduction of new airline routes. Given these intricacies, I propose a novel instrumental variable: the realized traveling population. This measure acts as a broad proxy for ease of travel. I use the cell phone signal data to calculate the monthly count of passersby who happen to pass through both the VC and startup buildings⁵. This count, in turn, serves as an instrumental variable for the intensity of VC's monitoring activities. Consider months with frequent heavy rain, which lead to fewer individuals strolling between the VC and startup buildings. Such unfavorable travel conditions might also discourage VCs from regular monitoring visits. The first-stage regression results support the likely satisfaction of the inclusion condition, revealing that the number of passersby strongly predicts the frequency

⁵To ensure that the correlation between the IV and the monitoring intensity isn't driven by potential misidentification of VC employees versus passersby, I distinguish between cell phone data from weekdays and weekends. Specifically, the IV is based on cell phone signals captured during non-working hours and weekends from individuals unaffiliated with either VCs or startups. This stands in contrast to the monitoring measure, which is constructed using cell phone signals from likely VC employees during regular working hours.

of VC-startup meetings, with F-statistics well above 10.

The exclusion condition of the IV appears to be satisfied: These passersby, merely random individuals traveling in the vicinity, have no direct relevance to the VCs and startups. Hence, the number of passersby — serving as an indicator of travel ease between VC and startup locations — is unlikely to directly influence the subsequent performance of a VC's deal. However, to argue that this IV is valid, it's vital to further ensure that the number of passersby is not correlated with unobserved factors that could be associated with both the monitoring activities and subsequent deal performance. A plausible concern is the effect of local shocks, such as a local economic boom in the VC's or the portfolio company's area. For instance, a thriving local economy in the VC's region could simultaneously enhance the VC's subsequent deal performance and increase the number of passersby, suggesting a spurious result. However, since the IV captures travel ease at the VC by portfolio company by month level, I can control for such local shocks. Specifically, I include both VC city by month and startup city by month fixed effects. Additionally, I incorporate VC-startup pair fixed effects to control for the distance between VC and startup buildings and any other time-invariant characteristics specific to each VC-startup relationship. This approach provides a stronger argument for the exclusion restriction of the IV.

Utilizing a two-stage least squares (2SLS) regression, I examine the relationship between a VC's monitoring activities and the quality of its future deals. Monitoring activities are quantified by the number of meetings between a VC and a portfolio company in a month. Baseline regression results indicate that increased monitoring activities enhance VCs' likelihood of investing in future unicorns. Specifically, if a VC doubles its monitoring intensity, then for the next year, the probability that this VC invests in a startup that eventually becomes a unicorn (unicorn spot rate) will increase by 2.74 percentage points. Considering that the average unicorn rate in the VC industry is about 2.8%, this implies that doubling the frequency of meetings with startups can potentially double the number of unicorns a VC invests in, while maintaining the same investment level.

What are the economic mechanisms behind the main result? One hypothesis is the reputation channel (Winton and Yerramilli (2021)). More frequent interactions with entrepreneurs enhance the VC's reputation, facilitating easier matches with preferred entrepreneurs. In practice, when approaching new entrepreneurs, VCs often encourage them to speak with their existing portfolio companies. This allows entrepreneurs to assess the VC's value-adding contributions firsthand. Consequently, VCs known for providing substantial support gain popularity through word-of-mouth, further enhancing their reputation for future investments. Aligning with this anecdotal industry evidence, my findings reveal that

increased monitoring aids VCs in better matching with seasoned entrepreneurs in the deals they engage in the following year. Specifically, if a VC doubles its monitoring intensity, in the following year, the VC is more likely to attract CEOs with an additional 8 months of prior founding experience. In light of the VC industry's preference for seasoned or serial entrepreneurs, these findings suggest that increased monitoring boosts a VC's reputation, leading to better matches with elite entrepreneurs.

In addition to the main findings, I present descriptive results in Section 3, outlining eight stylized facts about VC monitoring. As the dataset comprises detailed monitoring activities across 150,000 deals over a span of five years in the US, these descriptive results should be considered representative of the VC industry as a whole, not merely a subsample. Some of these results confirm familiar anecdotal evidence, such as the correlation between monitoring frequency and proximity, and increased monitoring of underperforming portfolio companies. Other findings offer new insights into the VC industry. For instance, Private Equity firms, Corporate Venture Capital, and VCs exhibit similar monitoring intensity, and larger VC firms conduct more total meetings, but fewer on a per-deal basis. This descriptive section validates the data and supplements the main findings of the study.

This study contributes to a large literature that studies the effect of VC monitoring activities. Early works, including those by Sahlman (1990) and Gorman and Sahlman (1989), provide valuable descriptive facts about monitoring activities, illustrating how VCs invest significant time in portfolio companies, mentoring founders, and delivering strategic guidance. Hsu (2004), using hand-collected data from startups with multiple VC offers, reports that despite lower valuations, high-reputation VCs are preferred by entrepreneurs due to their value-adding role. Further expanding upon these observations, several studies have examined VC involvement in portfolio companies' CEO replacement (Lerner (1995), Hellmann and Puri (2002), Wasserman (2003), Kaplan et al. (2012)). Meanwhile, another stream of literature explores the effect of value-adding activities on the performance of portfolio companies, specifically the likelihood of successful exits. Bottazzi et al. (2008) find a positive correlation between active VC involvement and successful exits. However, a common challenge in these studies is disentangling selection from treatment effects. To address this, Sørensen (2007) uses a two-sided matching model to estimate the relative importance of VC monitoring and screening. Bernstein et al. (2016) exploit an exogenous shock in airline routes to identify the causal effect of VC monitoring on portfolio companies' innovation and exit outcomes. In contrast to these prior studies, this paper shifts the focus to the impact of VC monitoring on VCs themselves, rather than on the portfolio companies.

This paper also contributes to the expanding literature that utilizes cell phone-related

data to augment traditional datasets and demonstrates how the increasingly available information on individual digital footprints provides a picture of social activities. Prior research has leveraged digital footprints to explore various areas such as urban development (Bailey et al. (2018b); Glaeser et al. (2018)), housing decisions (Bailey et al. (2018a)), households' responses to income shocks (Baker (2018)), acquisitions (Testoni et al. (2022)), political aspects (Chen and Rohla (2018); Bizjak et al. (2022); Chen et al. (2022)), innovation (Atkin et al. (2022)), entrepreneurship (Jeffers (2019)), and the labor market (Barwick et al. (2023)). The existing studies using similar technology confirm its legal and acceptable use within academic research. This paper employs similar telecommunication technology, but uniquely applies it to the VC context, building a comprehensive dataset to analyze monitoring activity.

The structure of this paper is as follows: Section 2 discusses the data and key variables. Section 3 presents stylized facts about monitoring, derived from the data. Section 4 describes the empirical strategy. Section 5 displays the results. Section 6 concludes.

2. Data

2.1. Data Source and Sample Selection

In the pursuit of investigating VC monitoring activities, I utilized a unique methodology to create a dataset. I analyzed cell phone signals within a 200-meter radius around VC and startup office buildings from 2018 to 2023. This technology delivers location information precise up to 15 meters, along with timestamps, collected when an app is either active or running in the background.

All cell phone signals within a 2-mile radius of VC and startup office buildings were initially captured. These signals provided longitude and latitude data. Using the Google Maps API, I converted the addresses of the VC and startup offices into corresponding coordinates. This facilitated the manual calculation of the distance between each signal and the office buildings. For the baseline regression, I employed a 200-meter cutoff. Signals beyond this range were discarded, while those within were retained. I further refined the data in robustness checks, narrowing the cutoff to 100 meters and in some scenarios, to just 50 meters.

The construction of the dataset progressed through two main phases:

First, the objective was to identify devices likely belonging to VC employees. One key

method to differentiate VC employees from passersby was based on the frequency and timing of a device's appearance near the VC office. I presumed that an employee's device would frequently be detected near the office during standard working hours, which are from 8 am to 5 pm. Given that a typical month has around 20 working days, a device detected in the vicinity of the VC office for over 10 of those days was tagged as likely belonging to an employee. For further verification, I tested both stricter criteria (15 working days) and more lenient ones (5 working days).

Second, for detecting potential meetings between VCs and their portfolio companies, I used the proximity and duration of the device's presence near the portfolio company's office as a benchmark. If a device, previously identified as probably belonging to a VC employee, was detected within 100 meters of a related portfolio company's office during working hours and remained there for at least 10 minutes, it was considered as a potential meeting.

Anticipating possible complications due to multi-tenant buildings, I constructed a subsample where each VC firm and startup were the only entities in their respective buildings. This served as a robustness check.

With regards to data coverage, the fundamental approach involved sourcing user location data from a wide array of applications. The data provider incorporated more than 1,000 of the most widely used apps, observing 250 million unique devices at least once a month. Given the estimated population of 260 million smartphone users in the United States, the dataset accounts for almost 95% of the monthly active users. In comparison to the coverage offered by PitchBook, my dataset encompasses all active deals since 2017, excluding those that lacked valid addresses for either the VC firms or startups. Ultimately, the dataset, comprising over 150,000 deals between 10,000 investors and 30,000 portfolio companies, fortifies the robustness of the subsequent analysis.

2.2. Variables

2.2.1 Independent Variables

In my study, the primary variable is the monitoring intensity, measured by the frequency of meetings between the venture capital (VC) firm and the startup. For data construction, I define a 'meeting' as an instance when a cellphone, possibly belonging to a VC employee, is detected within a 100-meter radius of the portfolio company for more than 10 minutes. To test the robustness of this definition, I also apply proximity thresholds of 200 meters and 50 meters in my robustness tests. This approach allowed me to calculate the monthly meeting

frequency for each deal from January 2018 to January 2023.

The choice of 2018 as the starting point was based on the maturity of the tracking technology used, which only became sufficiently reliable in that year. Any data prior to 2018 is considered less robust due to the immaturity of the technology during those times. Even gathering data from as far back as 2018 posed significant challenges because of the high costs associated with storing and managing such voluminous historical records. In fact, most of the data available on the market can only reliably track back to 2021. This monthly meeting frequency serves as my main independent variable, and the data is structured at a deal-month level.

2.2.2 Dependent Variables

To measure the subsequent performance of startups, I employ several dependent variables, each sourced from different databases. My first source is CB Insights, from which I track startup outcomes using a unique measure called the Mosaic score.

The Mosaic score is a product of CB Insights, developed with initial support from the National Science Foundation. It is a composite measure that assesses a startup's health and its potential for future success. This score encompasses four distinct models, referred to as the 4Ms - Momentum, Market, Money, and Management.

Momentum: This model captures several volume and frequency signals, such as news/media coverage, sentiment, partnership and customer momentum, and social media activity. These signals are evaluated on an absolute and relative basis compared to industry peers and benchmarks.

Market: This model assesses the potential and health of the market or industry a company operates in. It considers factors like the number of companies in an industry, financing and exit momentum in the space, and the overall quality and quantity of investors active in that field.

Money: This model aims to determine the financial health of a company. It examines elements like burn rate, the quality and quantity of the investors, and the company's financial position relative to its industry peers and competitors.

Management: This is the most recent addition to the Mosaic model. It focuses on the founding and management teams at private tech companies. The model considers aspects like previous exits, funding rounds, industry experience, educational background, and the professional network of the management team.

Each of the 4Ms is scored on a scale of 0-1000, and these scores collectively contribute to the overall Mosaic score, also measured on a 1000 point scale, with 1000 representing the best score. Successful companies tend to have higher Mosaic scores than unsuccessful ones. In the context of my study, the Mosaic score from CB Insights serves as a dependent variable, capturing the subsequent performance of startups.

The second source for my dependent variables is PitchBook, a comprehensive database for the private equity and venture capital sectors. Here, I employ four unique measures.

Unicorn Status: This identifies whether a startup eventually becomes a unicorn, a company with a pre-money valuation exceeding 1 billion dollars in a funding round. PitchBook maintains records of pre-money valuations for a substantial portion of deals, allowing for the determination of unicorn status. Approximately 1,300 startups attained unicorn status.

Previous CEO Experience: I compute the total number of months the startup's CEO has previous experience as a CEO prior to the current firm. If the CEO has no prior CEO experience, this measure is set to 0. Existing literature suggests that VCs favor CEOs with more experience. Therefore, if a VC that conducts rigorous monitoring can match with startups led by more experienced CEOs, it could indicate that monitoring helps VCs build their reputation among startups.

Probability of Exit Outcomes: PitchBook's VC Exit Predictor, released in 2023, leverages machine learning to objectively assess a startup's chances of a successful exit. It predicts whether a VC-backed startup will be acquired, go public, or not exit due to failure or self-sustainability. To form this prediction, it considers company details like patents, industry, employee count, and news coverage, as well as deal activity and investor profiles. Trained on 46,000 observations, it was able to predict success (M&A and IPO) versus no exit outcomes at a 75% accuracy rate. This probability can help demonstrate if VCs that monitor more have better exit outcomes.

Opportunity Score: The final measure is an "opportunity score", calculated by Pitch-Book. This score is a percentile that indicates the likelihood of a high return on investment, aiding investors in identifying potential investment opportunities. The score is computed based on the predicted exit probabilities from a classification model trained on more than 64,000 observations of startups. The score considers all relevant and available information in the PitchBook database, with the intention of scoring companies at scale to assist investors in their decision-making processes. Companies ranked in the top decile based on this score were found to be 3.8x more likely to successfully exit via merger or public listing than those in the bottom 90%.

Thus, the Mosaic scores, Unicorn status, Previous CEO experience, Probability of exit outcomes, and Opportunity Score, sourced from CB Insights and PitchBook, serve as dependent variables in my study, allowing for a comprehensive analysis of a startup's subsequent performance.

2.2.3 Instrumental Variables

The instrumental variable (IV) used in this paper is the traveling population between the venture capitalist (VC) and the portfolio company building. This data was constructed in a similar method as the independent variable. To distinguish random passersby from VC employees, only the traveling population over the weekend is considered. This strategy mitigates the risk of including similar cell phone signals in both the IV and the independent variable, which measures on-site VC involvement typically scheduled during weekdays. Ensuring this IV doesn't contain the same information as the independent variable is essential to prevent the same omitted variable bias as the original regression.

Although the IV is constructed to avoid any common cell phone signals with the independent variable by definition, the inclusion condition may still hold. For instance, favorable weather may prompt more travel and more ad-hoc VC visits to nearby startups. Therefore, the number of random weekend passersby may predict VC's monitoring intensity. While not completely random, this variation could stem from exogenous sources, such as weather conditions, making it a potential exogenous source of variation.

In terms of exogenous shocks for monitoring, Bernstein, Giroud, and Townsend (2016) used the introduction of a new airline route as an exogenous shock. Theoretically, I could create a similar IV using a comparable airline shock. However, the current traveler IV seems to better fit my dataset, considering its granular data between two buildings. Employing an IV at a broader metropolitan statistical area (MSA) level, as done by Bernstein, Giroud, and Townsend (2016), might compromise the richness of my data.

Table 1 presents the summary statistics for the dependent, independent, and instrumental variables used in the primary regression. It's essential to note that the choice of criteria can result in different sample sizes. In my baseline regression, I apply stringent criteria: I include only cell phone signals detected within a 50-meter radius of a building, consider a device as an employee device if it appears for at least 15 working days within a month, and recognize an

event as a meeting only when a potential VC employee remains near the associated portfolio companies' buildings for at least 60 minutes. While this strict approach significantly reduces the risk of misinterpreting irrelevant passersby signals as VC monitoring events, it might also unintentionally exclude genuine signals indicative of actual VC monitoring activities. For example, even though a VC employee might typically be at work around 20 days per month, there could be days when their device doesn't send signals due to inactive background apps. This is especially plausible in the post-Covid era when remote work became more prevalent, leading to infrequent office visits. Furthermore, the criteria might miss shorter, impromptu 30-minute meetings. In the robustness check section, I test alternative criteria.

Table 1 Summary Statistics

This table presents summary statistics. Observations are at the deal-by-month level. Each variable is briefly defined as follows: logX represents the logarithm of the count of visits between the VC and the portfolio company for a specific deal within a given month. For certain VC-startup pairs, while I can observe VC monitoring under less strict criteria, no visits are observed under this stringent criteria, leading to a recorded value of 0. If VC monitoring isn't observed under any criteria, it's recorded as NaN, and the observation is dropped. logIV denotes the logarithm of the count of passersby traveling between the VC location and the portfolio company location during weekends. *Experience* and *newunicorn* characterize the quality of the portfolio companies that the VC invests in within 1 or 2 years after the current monitoring month. These measures are not the measure for the current deal. *Experience* is the total number of months the startup's CEO has previous experience as a CEO prior to the current firm. If the CEO has no prior CEO experience, this measure is set to 0. *newunicorn* indicates the count of portfolio companies that hadn't reached a 1 billion dollar post-money valuation at the time of investment but subsequently attained unicorn status, surpassing a 1 billion pre-money valuation in a later financing round.

Variables	Obs	Mean	Std	25%	50%	75%	
Panel A. Independent Variable and Instrumental Variable							
log_X	$92,\!912$	1.690	1.772	0.000	1.386	3.091	
log_IV	$3,\!012,\!532$	2.206	2.247	0.000	1.609	3.689	
Panel B. Dependent Variables							
_0_to_12_avg_Experience	32,313	17.563	29.452	0.000	4.899	23.567	
$_0_to_12_avg_newunicorn$	$32,\!646$	0.034	0.109	0.000	0.000	0.000	
$_0_to_24_avg_Experience$	$33,\!612$	17.855	28.725	0.000	6.677	24.456	
$_0_to_24_avg_newunicorn$	$33,\!964$	0.032	0.103	0.000	0.000	0.000	

3. Stylized Facts of Monitoring

In this section, I utilize the comprehensive dataset delineated in the preceding section to construct a series of graphical illustrations, aimed at unveiling some features of VC monitoring activities. These graphs offer an illustration of trends that, until now, have primarily been alluded to in anecdotal form within the extant literature. These visual analyses serve dual purposes: they not only illuminate these relationships but also act as a critical sanity check for my data, affirming its consistency and suitability for further examination. The insights derived from these graphs will not directly feed into the regression analyses of the ensuing section but rather provide an empirical foundation for our understanding of VC monitoring practices.

Figure 1, Figure 2, and Figure 3 provide compelling evidence that VCs tend to monitor underperforming portfolio companies more frequently.

Figure 1 uses three distinct measures to rank portfolio companies based on their performance. The first measure, the probability of exit, is derived from PitchBook's VC Exit Predictor, which leverages machine learning to objectively assess a startup's chances of achieving a successful exit as of April 2023. This probability can be seen as an indicator of the overall performance and potential success of the portfolio company. The second measure, the Opportunity Score, is a percentile ranking that represents the potential for a high return on investment. The higher the Opportunity Score, the greater the likelihood of the company's successful exit via merger or public listing. The third measure, the Mosaic Score, is an indicator developed by CB Insights that measures a startup's health and potential for future success. This score incorporates multiple factors, including financial health, business model viability, and market dynamics. Each of these measures demonstrates a downward trend in the graph, suggesting that companies with lower performance scores tend to have more frequent meetings with VCs.



Figure 1. Performance and monitoring intensity. The figure illustrates that VCs tend to have more frequent meetings with portfolio companies that perform worse, indicating an inverse correlation between portfolio companies' performance and the number of total meetings conducted with VCs. The leftmost subplot utilizes the probability of exit to gauge portfolio companies' performance. This metric, derived from PitchBook's VC Exit Predictor, utilizes machine learning to objectively evaluate a startup's chances of achieving a successful exit as of April 2023. Higher exit probabilities suggest superior performance from the portfolio company. The middle subplot employs the Mosaic score as the measure, a product of CB Insights that evaluates a startup's health and potential future success. A high Mosaic score suggests promising performance. The rightmost subplot utilizes the Opportunity Score from PitchBook. This score is a percentile that indicates the likelihood of a high return on investment. Companies ranked in the top decile based on this score were found to be 3.8x more likely to successfully exit via merger or public listing than those in the bottom 10%. Higher scores symbolize enhanced performance. Detailed descriptions of these measures can be found in Section 2.2.2.



Figure 2. Number of Meetings with Unicorns vs. Non-Unicorns. The figure compares the number of monthly meetings held by venture capitalists with unicorn portfolio companies versus non-unicorn companies. A unicorn portfolio company is defined as a company that has achieved a pre-money valuation of at least 1 billion dollars in any financing round as of April 2023.

Figure 2 further explores this trend by comparing the monitoring intensity for unicorns and non-unicorns. Unicorns, defined here as companies that have achieved a pre-money valuation of at least 1 billion dollars in any financing round as of April 2023, serve as an intuitive, binary measure of performance. I find that unicorn portfolio companies receive an average of 0.5 meetings per month, while non-unicorn companies have an average of 0.9 meetings per month, indicating that non-unicorn firms receive 80% more monitoring than unicorns. Upon aggregating the total number of meetings, I find that only 5.1% of the meetings are between VCs and unicorns, while the remaining 94.9% are between VCs and non-unicorns. This observation is intriguing when considering that the small percentage of unicorns generate the lion's share of profits for VCs.



Figure 3. Monitoring intensity and profits for portfolio companies with different exit multiples. The figure delivers a side-by-side comparison of the monitoring 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: <1x, 1-2x, 2-5x, 5-10x, and >10x. The monitoring measure, represented in the first bar, indicates the percentage of total meetings conducted by VCs and their portfolio companies. The monitoring measure is derived from the main dataset in this paper, while the exit multiple information is sourced from CB Insight. The second bar showcases the profit shares of each category, with data reported from 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 3 conveys the contrast between the intensity of monitoring efforts and the corresponding profits across different categories of portfolio companies, categorized by their exit multiples, ranging from <1x to >10x. As clearly shown in the figure, VCs derive over 90% of their profits from the "home runs" – portfolio companies that yield exit multiples ten times or greater. However, these high-performing portfolio companies receive less than 5% of the total monitoring resources from VCs. This imbalance highlights the disconnect between monitoring intensity and the primary profit source for VCs, thus motivating the central research question of this paper: why do VCs allocate significant time and resources to monitoring portfolio companies, if the primary source of their profits does not correlate directly with these efforts?



Figure 4. Distance and monitoring intensity. This figure illustrates the correlation between the distance (measured in kilometers) between a venture capitalist's (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 4 provides a comprehensive depiction of the relationship between distance and monitoring intensity. Each circle in the graph represents the average monthly meeting frequency for each half-kilometer interval of distance between the VC and the portfolio company. The left panel focuses on deals where the distance is less than 20 kilometers. In this range, the intensity of monitoring shows a pronounced sensitivity to distance. For instance, when the VC and the portfolio company are only 5 kilometers apart, the VC visits the portfolio company once a month on average. However, as this distance increases to 10 kilometers, the average monitoring frequency drops to half a meeting per month. This inverse relationship between distance and monitoring intensity aligns intuitively with anecdotal evidence from the existing literature, and the comprehensive dataset used in this graph offers a formal validation of this relationship. Furthermore, the size of each circle reflects 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, corroborating the 'home bias' phenomenon extensively documented in the literature. The middle and right panels of the figure extend this analysis to VC-portfolio company pairs that are farther apart. For distances between 20 and 60 kilometers, the average number of monthly meetings is slightly above zero. However, for deals involving distances beyond 60 kilometers—approximately an hour's drive—the number of meetings approaches zero. This indicates that beyond a certain distance, the intensity of monitoring becomes insensitive to further increases in distance.



Figure 5. Financing rounds and monitoring intensity. This figure illustrates the relationship between the financing round of the deal and the average frequency of meetings per month between the venture capitalist (VC) and the portfolio company throughout the course of the deal.

Figure 5 sheds light on the relationship between the financing round of a deal and the intensity of monitoring by the VC. For each deal, the average frequency of monthly meetings from the deal initiation date to the end of the sample period is computed. As the figure illustrates, seed round deals are subject to the highest level of monitoring, with VCs meeting with portfolio companies an average of 1.3 times per month. As the financing round progresses from Series A through to Series E, the frequency of these meetings gradually decreases. On average, VCs engage in monitoring activities around 0.8 times per month for Series E deals. This suggests that early stage deals experience a 62.5% higher level of monitoring intensity compared to late-stage deals. This trend aligns intuitively with the nature of early-stage startups. As these companies are typically less mature and have less established business operations, VCs are motivated to meet with them more frequently to provide guidance and closely monitor their operational status. As a portfolio company advances to later stages, the need for intensive monitoring and learning about the startup by the VC diminishes, leading to a corresponding decrease in the frequency of meetings.



Figure 6. Monitoring 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 6 elucidates the variations in monitoring intensity across different types of investors. As the figure demonstrates, accelerators and incubators engage in the most frequent monitoring activities, with an average of 2.5 meetings per month. Given that these entities typically invest in early-stage startups, which require higher levels of monitoring and support, this heightened level of monitoring activity is not unexpected. The remaining investor types exhibit similar levels of monitoring intensity. Angel investors, VCs, private equity (PE) firms, and corporate venture capital (CVC) entities typically meet with their portfolio companies approximately once a month. Hedge funds, on the other hand, demonstrate a slightly lower level of on-site involvement, with an average of 0.8 meetings per month. The figure thus reveals a pattern in which early-stage investors (such as accelerators and incubators) engage in more frequent meetings with entrepreneurs, while other investor types typically meet with their portfolio companies about once a month.



Figure 7. Co-investors and monitoring intensity. This figure illustrates the average monthly meetings between the VC and the portfolio company for deals involving different numbers of investors. The size of each circle indicates the number of observations.

Figure 7 depicts the relationship between the number of investors in a deal and the monitoring intensity of each investor. For deals involving a single investor, the investor meets with the portfolio company an average of 1.7 times per month. However, as the number of co-investors in a deal increases, each investor tends to spend less time monitoring the portfolio company. The average monthly meetings drop to 1.3, 1.2, and 1.1 for deals with 2, 3, and 4 investors, respectively. Interestingly, although the number of meetings for each investor decreases as the number of investors increases, the total number of meetings between VCs and the portfolio company actually rises. This suggests that there is no free riding issue among syndicate VCs, consistent with the existing literature that posits that the presence of a lead investor mitigates such concerns. Overall, the figure provides empirical evidence supporting the assertion that the structure of syndicate deals helps to prevent free-riding among investors.



Figure 8. Time trend of VC monitoring. This figure presents the monitoring intensity from two years before to two years after the deal. The data is derived from deals in 2020 to ensure a comprehensive view. The intensity is gauged by the number of VC meetings with the portfolio company. The monitoring intensity increases as the deal date approaches, dips briefly post-deal, peaks at six months post-deal, declines, and then rises again at 18 months post-deal, suggesting a pattern of VC monitoring activities in relation to the deal timeline.

Figure 8 offers a temporal perspective on the dynamics of venture capital monitoring activities. Spanning from two years pre-deal to two years post-deal, this figure captures the monitoring intensity, represented by the number of meetings between the venture capitalist and the portfolio company. Notably, the data is rooted in the deals enacted in 2020, providing a holistic insight into the monitoring process. In the lead-up to the deal date, a gradual uptick in monitoring intensity is observed, indicative of increased interaction between the VC and the portfolio companies. Post-deal, the monitoring intensity undergoes a minor slump. This may be attributable to the VC having gathered substantial information during the due diligence process prior to the deal, with minimal alterations in the immediate aftermath. However, six months post-deal, a surge in monitoring intensity is observed, reaching over 0.20. This suggests that, on average, in 20% of the deals, the VC revisits the startup during the 6th-month post-deal, possibly to assess updates and progress. Subsequent to this peak, the monitoring intensity enters a phase of decline. Interestingly, 18 months post-deal, another increase in monitoring intensity is discernible. This spike may be linked to the VC's monitoring activities in anticipation of the next financing period. These time-based trends in monitoring intensity provide valuable insights into the VC's monitoring strategy and its correlation with the deal timeline.



Figure 9. The number of VC partners and monitoring intensity. The top subplot shows the total number of meetings between a VC and its portfolio companies during the monitoring period, while the bottom subplot illustrates the average number of meetings per deal per month for a VC.

As depicted in Figure 9, the relationship between the number of VC partners and monitoring intensity presents an intriguing dichotomy. The top subplot illustrates that as the number of partners within a VC firm increases, the total monitoring intensity, as evidenced by the number of meetings, also rises. This suggests that larger firms, with a greater number of senior-level staff, may have the capacity for increased engagement with portfolio companies. However, the bottom subplot tells a slightly different story. It reveals that the average monitoring intensity per deal per month decreases as the number of VC partners grows. This indicates that while larger VCs may have more overall meetings, the average number of meetings per deal per month reduces, suggesting that these firms distribute their attention across a larger portfolio of companies.

Figure 10 provides a close look at the relationship between the size of a portfolio company, measured by the number of startup employees, and the intensity of investor monitoring. Each point on the graph corresponds to a portfolio company, and the graph employs a binned scatter plot approach, averaging points within the same interval. The figure reveals a clear trend: as the size of the portfolio company increases, so does the total number of meetings with all investors. This suggests that larger companies, with more employees, attract higher levels of engagement and scrutiny from investors, possibly due to their more complex operations or higher stakes involved.



Figure 10. The number of startup employees and monitoring intensity. The graph represents the total number of meetings with all investors post the deal date for each portfolio company, sorted by the number of startup employees.

4. Methodology

This study employs an instrumental variable (IV) approach to investigate the causal relationship between venture capitalist (VC) monitoring activities and investor performance, tackling potential endogeneity issues. The instrumental variable employed is the volume of passersby traveling between the VC and startup locations during the weekend, while the independent variable is the intensity of VC monitoring activities. Higher numbers of passersby, potentially influenced by exogenous factors such as favorable weather conditions, indicate easier travel, thus providing an exogenous source of variation for monitoring activities. To provide a comprehensive understanding of this methodology, I first present a case study in San Francisco to provide a tangible understanding of the IV. Following this, I establish the relationship between the IV and the independent variable for the full sample. Finally, I outline the regression format used in this study.

4.1. A Case Study in San Francisco

This subsection presents a case study to provide more intuition for the IV. Figures 14 and 15 in the Appendix illustrate the foot traffic of passersby and VC visits in the San Francisco area for July and August 2021, respectively. Portfolio companies are denoted by red dots, while VC locations are marked by blue dots.

In Figure 14, the green lines represent the total unique passersby traveling between the VC and startup locations over the weekends of the respective month. The line width is proportional to the number of passersby, adjusted to a common scale (normalized), with a wider line indicating a higher volume of travel. These lines are only displayed for active VC-portfolio company pairs, aligning with the independent variable measure.

Meanwhile, Figure 15 represents the total number of weekday meetings between the VC and the startup for the respective month. The line width here is proportional to the normalized number of meetings, with a wider line indicating more VC meetings. It's important to note that the line width should be compared within each graph across different months, not across graphs, due to the difference in the scale of line widths used in each figure.

To gain more insight into the IV, we focus on the travel between downtown San Francisco and the Palo Alto region, a notable hub for venture capital firms. As depicted in Figure 14, July saw a significant flow of people traveling between these two regions. However, this flow significantly diminished in August. This pattern is mirrored in Figure 15, with a high volume of VC meetings in July that significantly reduced in August. This correlation suggests a potential influence of external factors on both passersby and VC meetings.

An investigation into the weather conditions in San Carlos, located midway between San Francisco and Palo Alto, revealed significant changes between July and August. While July had no abnormal weather conditions during working hours, August experienced 10 days of haze, mist, and smoke, primarily during working hours on weekdays, as shown in Figure 15. This adverse weather may have discouraged travel between the two locations, explaining the observed correlation.

This case study serves as a motivating example of a potential random weather shock occurring en route from the VC building to the startup's building. This exogenous variation on the route, essentially on VC by portfolio company by month level, would not be absorbed by adding VC by month and portfolio company by month fixed effects. This underscores the validity and usefulness of this IV strategy.

4.2. Exploring the Correlation Between Passersby Traffic and VC Meetings

Figure 11 below illustrates the relationship between the IV and the independent variable by plotting the raw data of traveling passersby against the VC's monitoring activities.



Figure 11. The relationship between the number of passersby and meetings between VC and portfolio company locations. The graph represents the number of passersby (IV) and the number of meetings (X) for each VC-portfolio company active deal pair. Data is aggregated at deal-month level. The x-axis represents the number of unique devices traveling between the two locations, while the y-axis denotes the number of monthly meetings between the VC and portfolio company. Each circle in the graph represents the aggregate value within an interval; the larger the circle, the more deals within that interval.

As Figure 11 indicates, there is a strong positive correlation between the number of passersby during the weekend (IV) and the frequency of meetings during weekdays (X) for each VC-portfolio company deal pair. This suggests that the inclusion condition is likely to hold. Initially, there is a positive linear relationship between monitoring activity and the number of random passersby, indicating that VC visits are likely influenced by endogenous factors like distance, or exogenous factors such as weather conditions. However, when the monitoring intensity increases to 5 meetings per month, the monitoring intensity presents a lower slope in relation to the number of passersby. The graph's logarithmic-like relationship also hints that using the log of meetings as the independent variable might provide stronger predictive power in the first stage. Building on this intuition, and to more effectively capture the sensitivity of the outcome variable to a 1% change in monitoring activities, I employ the logarithmic form of X and IV in the baseline regression. In the robustness check section, I show that the level form of these variables provides similar results to the log form in terms of sign and significance.

Figure 12, meanwhile, shows the relationship between the number of passersby and the monthly meetings after incorporating VC and portfolio company fixed effects, and month fixed effects. Even after controlling for fixed effects, a positive correlation between the independent variable and the IV remains, reaffirming the likelihood of satisfying the inclusion condition when incorporating fixed effects into the regressions.



Figure 12. Relationship between residuals: number of passersby versus the number of meetings between VC-portfolio company locations. The graph represents the number of passersby (IV) and the number of meetings (X) for each VC-portfolio company active deal pair, after adding control variables. The residuals from regressing both the number of passersby and the number of meetings against fixed effects are plotted here. The four graphs display full data, the 25% to 75% percentile, the 35% to 65% percentile, and the 40% to 55% percentile.

4.3. Regressions

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:

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

where *i* indexes VC firms, *j* indexes portfolio companies, *t* indexes months, location(i) and location(j) represent the locations of VC *i* and portfolio company *j* respectively. Monitoring is the monthly visits between the VC and the portfolio company. α_{ij} are VC-portfolio company fixed effects, while $\alpha_{location(i)} \times \alpha_t$ and $\alpha_{location(j)} \times \alpha_t$ are city-by-month fixed effects. η_{ijt} is the error term.

The second stage regression is:

$$y_{i,t+12} = \beta_0 + \beta_1 Monitoring_{ijt} + \alpha_{location(i)} \times \alpha_t + \alpha_{location(j)} \times \alpha_t + \alpha_{ij} + \epsilon_{ijt}$$
(2)

where $Monitoring_{ijt}$ is the fitted value of the monitoring measure from the first-stage regression. $y_{i,t+12}$ is the dependent variable of interest, capturing the quality of the subsequent portfolio companies that the VC associates with, within a 12-month timeframe following the monitoring activities. In both the main regressions and the robustness checks, I also consider alternate timespans ranging from 0 to 24 months. It's worth noting that this regression structure isn't a standard panel data IV regression, as the dependent variable in the second stage isn't about the current portfolio j, but instead concerns future portfolio companies. As such, the dependent variable is not at the ijt level. Portfolio company measures include unicorn status and CEO experience. I incorporate the same fixed effects in the second stage as in the first. β_1 captures the impact of monitoring on the quality of subsequent VC deals.

This methodology 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 level. In Sections 5.1 and 5.2, I present the main results derived from the deal-by-month level regression as outlined above. To demonstrate the robustness of these results, I also apply deal-level and VC-by-month level regressions. The corresponding results of these additional analyses are provided in Section 5.3.

5. Results

In this section, I use two-stage least squares (2SLS) regressions to estimate the impact of monitoring on the quality of a VC's future deals. Section 5.1 presents the primary regression results, utilizing the subsequent unicorn rate as the dependent variable to measure deal quality. Section 5.2 further explores the potential channel behind the main results. To ensure the robustness of these findings, Section 5.3 conducts a series of checks, employing various filters, alternative independent and dependent variables, and alternative regression models.

5.1. Main Results

This section presents the detailed results of the main regression, exploring the impact of VC monitoring activities on the unicorn rate of their future deals.

The second stage results of the 2SLS regression are presented in Table 2. Column (1) reports the impact on the quality of future deals within one year after the monitoring activities. The coefficient is 0.0274, suggesting that if a VC increases its monthly meetings with all portfolio companies by 1% at a given time, then, within the following year, any new investment the VC makes will have a 0.0274% higher likelihood of being in a startup that eventually attains unicorn status. In other words, if the VC doubles its monitoring effort, then the unicorn spot rate will increase by 2.74 percentage points. This is a significant improvement, given that the average unicorn rate for all the VCs with at least 10 investments is about 2.8%, this result implies that doubling the frequency of meetings with startups can potentially double the number of unicorns a VC invests in, while maintaining the same investment level. Columns (2), (3), and (4) report similar results, with differences in the inclusion of startup city by month FE and the timespan. Overall, this table shows that the change in monitoring activities has a significant influence on the quality of subsequent deals

Table 2The Impact of VC Monitoring on the Unicorn Rate of Future Deals

This table presents the second-stage result of the 2SLS regression, examining the impact of VC monitoring on the unicorn rate of future deals. Observations are at the deal-by-month level and include only deals in the sample for which at least one visit was observed during the entire sample period. The independent variable, logMonitoring, represents the logarithm of the count of visits between the VC and the portfolio company for a specific deal and month. The dependent variable, NewUnicorn, denotes the rate of portfolio companies, which have not reached a 1 billion dollar postmoney valuation at the time of investment, but later achieved over 1 billion pre-money valuation in a financing round. This dependent variable reflects the average quality of all the subsequent portfolio companies that the VC invests in, measured across different time periods (1 year or 2 years) following the current month, rather than the unicorn rate for the current deal. PairFE refers to the VC by portfolio company fixed effect. CitybyMonthFE includes the VC headquarter's city by month fixed effect and the portfolio company headquarter's city by month fixed effect. Kleibergen – PaapWaldF – stat reports the F-statistics on the first stage regression. Standard errors are clustered by VC and are indicated in parentheses. The asterisks *, **, and *** signify statistical significance at the 10%, 5%, and 1% levels, respectively.

	NewUnicorn				
	1 year		2 ye	ears	
	(1)	(2)	(3)	(4)	
log Monitoring	0.0274^{*}	0.0272^{*}	0.0301**	0.0299**	
	(0.0166)	(0.0161)	(0.0134)	(0.0131)	
Observations	$29,\!120$	$29,\!384$	$30,\!250$	$30,\!529$	
Pair FE	Yes	Yes	Yes	Yes	
VC City by Month FE	Yes	Yes	Yes	Yes	
Startup City by Month FE	Yes	No	Yes	No	
Kleibergen-Paap rk Wald F-stat	39.52	41.24	41.65	43.01	

Aside from the main results, Tables 3 and 4 report the first-stage results and a comparison with a naïve OLS regression, respectively. Table 3 demonstrates that the number of passersby strongly predicts the number of VC meetings, as evidenced by high t-statistics and F-statistics well above 10. The coefficient is positive, suggesting that the ease of travel positively affects VC visit patterns.

Table 3Main Regressions: First Stage Result

This table presents the first-stage results of the main regression. Each column corresponds to the exact columns in Table 2. Observations are at the deal-by-month level and include only deals in the sample for which at least one visit was observed during the entire sample period. In the first stage, the independent variable is logPassersby, representing the logarithm of the count of

passersby traveling between the VC and the portfolio company buildings. The dependent variable is logMonitoring, representing the logarithm of the count of visits between the VC and the portfolio company for a specific deal and month. The set of fixed effects is identical to those in the second-stage regression. *PairFE* refers to the VC by portfolio company fixed effect. *CitybyMonthFE* includes the VC headquarter's city by month fixed effect and the portfolio company headquarter's city by month fixed effect. Columns differ in their choice of fixed effects, and different choices of dependent variable in the second-stage results lead to different number of observations, which cause variations in the first-stage coefficients. Standard errors are clustered by VC and are indicated in parentheses. The asterisks *, **, and *** signify statistical significance at the 10%, 5%, and 1% levels, respectively.

	log Monitoring				
	1 y	ear	2 y	ears	
	(1)	(2)	(3)	(4)	
$\log IV$	0.168***	0.169***	0.165^{***}	0.165^{***}	
	(0.0268)	(0.0263)	(0.0256)	(0.0251)	
Observations	$29,\!120$	29,384	$30,\!250$	$30,\!529$	
Pair FE	Yes	Yes	Yes	Yes	
VC City by Month FE	Yes	Yes	Yes	Yes	
Startup City by Month FE	Yes	No	Yes	No	
Kleibergen-Paap rk Wald F-stat	39.52	41.24	41.65	43.01	

Table 4 displays the OLS regression results using the same set of fixed effects and dependent variables. Contrary to the 2SLS results, the OLS coefficients are insignificant and smaller in economic magnitude. This discrepancy is likely due to reverse causality or the omitted variable bias. One potential explanation could be that VCs with lower ability tend to invest in underperforming startups in the current period. These startups require more assistance, leading VCs to monitor them with greater intensity. Meanwhile, VCs with lower ability also tend to invest in underperforming startups in the future, creating a negative correlation between current monitoring intensity and the future performance of the VC. These two opposing forces counteract each other, resulting in an insignificant coefficient with a magnitude closer to 0. The OLS results underscore the necessity of addressing the endogeneity issue in this research question.

Table 4Main Regressions: OLS

This table is an OLS version of Table 2, presenting the impact of VC monitoring on the unicorn rate of future deals. Each column exactly matches the corresponding columns in Table 2 in terms of the choice of dependent variable time span and fixed effects, thus offering a direct comparison between the simple OLS result and the 2SLS outcome shown in Table 2. Observations are at the deal-by-month level and include only deals in the sample for which at least one visit was observed during the entire sample period. The asterisks *, **, and *** signify statistical significance at the 10%, 5%, and 1% levels, respectively.

	New Unicorn				
	1 year		2 ye	ears	
	(1)	(2)	(3)	(4)	
log Monitoring	0.00138	0.00138	0.00117	0.00118	
	(0.00173)	(0.00169)	(0.00123)	(0.00120)	
Constant	0.0340^{***}	0.0339^{***}	0.0319^{***}	0.0318^{***}	
	(0.00212)	(0.00208)	(0.00154)	(0.00151)	
Observations	$29,\!120$	$29,\!384$	$30,\!250$	$30,\!529$	
R-squared	0.666	0.667	0.748	0.749	
Pair FE	Yes	Yes	Yes	Yes	
VC City by Month FE	Yes	Yes	Yes	Yes	
Startup City by Month FE	Yes	No	Yes	No	

5.2. The Reputation Channel

This section examines the reputation channel hypothesis, which proposes that more frequent interactions with entrepreneurs can boost a VC's reputation, thereby facilitating easier matches with preferred entrepreneurs. The reputation-building process in the VC industry typically unfolds as follows. When a VC attempts to attract a new entrepreneur, the VC may facilitate a dialogue between the new entrepreneur and the CEOs of its existing portfolio companies. The new entrepreneur is then encouraged to inquire about the VC's accessibility, contributions to boardroom discussions, and the assistance they have offered in resolving company issues⁶. While it's challenging to quantify the quality of monitoring, the intensity of such monitoring and supportive activities can serve as a reasonable proxy. Therefore, a VC who visits portfolio companies more frequently may gain an edge in future negotiations with new entrepreneurs.

I use total number of months the entrepreneur has previous experience as a CEO prior to the current firm as a measure of the CEO experience. The existing literature suggests that VCs perceive serial entrepreneurs and CEOs with more experience as preferable. One advantage of using the CEO experience variable is that it's typically observable to all VCs before investment decisions are made, so pairing with an entrepreneur who is ex-ante desirable could be interpreted more as a reputation story rather than an outcome of the learning process.

⁶Mulcahy, Diane. "6 myths about venture capitalists." Harvard Business Review 91.5 (2013): 80-83.

The impact of monitoring on the CEO experience of future deals is presented in Table 5. Column (1) indicates that for startups in which VCs invest within one year following a monitoring activity, the CEOs are typically more experienced. Specifically, if a VC doubles its monitoring intensity, then in its investments the following year, the VC tends to attract CEOs who have an additional 8 months of prior founding experience. Column (2) yields a similar outcome but excludes the startup location by month fixed effects. Columns (3) and (4) explore the effect two years after monitoring, revealing significant yet diminished coefficients. This waning impact over time is intuitive, hinting that the reputation effect diminishes as time progresses.

Table 5The Impact of VC Monitoring on the CEO Experience of Future Deals

This table presents the second-stage result of the 2SLS regression, which examines the impact of VC monitoring on the CEO experience of future deals. Observations are deal-by-month level and include only deals in the sample for which at least one visit was observed during the entire sample period. The independent variable, *log Monitoring*, represents the logarithm of the count of visits between the VC and the portfolio company for a specific deal and month. The dependent variable, *CEO Experience* measures the total number of months the startup's CEO has previous experience as a CEO prior to the current firm. If the entrepreneur has no prior CEO experience, this measure is set to 0. This dependent variable reflects the average quality of all the subsequent portfolio companies that the VC invests in, measured over different time periods (1 year or 2 years) following the current month, rather than the experience of CEO for the current deal. *Pair FE* refers to the VC by portfolio company fixed effect. *City by Month FE* includes the VC headquarter's city by month fixed effect and the portfolio company headquarter's city by month fixed effect. *Kleibergen-Paap Wald F-stat* reports the F-statistics on the first stage regression. Standard errors are clustered by VC and are indicated in parentheses. The asterisks *, **, and *** signify statistical significance at the 10%, 5%, and 1% levels, respectively

	CEO Experience				
	1 year		2 ye	ears	
	(1)	(2)	(3)	(4)	
log Monitoring	7.998*	8.086^{*}	6.119*	6.306^{*}	
	(4.421)	(4.405)	(3.687)	(3.706)	
Observations	$28,\!822$	$29,\!086$	$29,\!928$	$30,\!203$	
Pair FE	Yes	Yes	Yes	Yes	
VC City by Month FE	Yes	Yes	Yes	Yes	
Startup City by Month FE	Yes	No	Yes	No	
Kleibergen-Paap rk Wald F-stat	37.32	38.63	38.77	39.92	

5.3. Robustness Checks

In this section, I test the robustness of the regression results and employ specification curves to illustrate these checks. The use of specification curves, increasingly prevalent in contemporary research, offers a succinct means of displaying the hundreds or even thousands of robustness tests supporting the main regression findings.

In Section 5.3.1, I evaluate the robustness of the primary findings across different data construction methodologies. In Section 5.3.2, I further explore the robustness by employing different levels of regressions – specifically, deal-level and VC-by-month level analyses, thus demonstrating the consistency of the main results under varying granularities of analysis. In Section 5.3.3, I test the robustness of the results against variations in the outcome and independent variables, and across differing timespans. Further specification curves are provided in the Appendix for those readers interested in delving into additional validation scenarios.

In summary, this section presents the results of regression analyses under a wide range of different specifications. The findings exhibit robust consistency, with the coefficient's sign, economic magnitude, and statistical significance maintaining stability across the vast majority of these specifications.

5.3.1 Alternative Data Construction Methods

In this section, the specification curve for the main regression in Section 5.1 is plotted. The regression, conducted at the deal-by-month level, uses *log Monitoring* as the independent variable and the future deals' average unicorn rates within 2 years post-monitoring as the outcome variable. As previously discussed, there are many different methods of data construction. For example, the main regression uses data constructed by the following criteria: A device is considered an employee device as long as it's been detected for a minimum of 15 working days in a month. Moreover, any event is classified as a visit if the duration of the stay exceeds 60 minutes. This strict criterion mitigates the risk of including irrelevant signals. However, it's plausible to question whether these significant results might simply coincide with this specific method of data construction. To test if the results are consistent across different monitoring measures, I plot Figure 13. The graph consists of two parts. The gray area in the bottom panel specifies the exact specification for each coefficient. Specifically, the graph includes regression results derived from various data construction methods: (1) Regression Type: incorporating either pair FE, VC city by month FE and startup city by month FE, or just pair FE and VC city by month FE. (2) IV Measure: only using the

number of weekend passersby or including passersby during non-working hours on weekdays. (3) Monthly Occur Filters: defining a device as an employee device if it's detected around the VC building for 15 or 20 working days in a given month. (4) Duration of Stay: considering a minimum stay of 1, 10, 30, or 60 minutes to count as VC monitoring activity. In total, 32 different combinations (2*2*2*4=32) were used to construct the dependent and instrumental variables. This graph shows all 32 second-stage coefficients. A red point signifies a statistically significant coefficient, with first-stage F-statistics exceeding 10, while blue bars represent the 95% confidence interval, taking into account clustered standard errors. All coefficients are positive and their magnitudes hover around 0.03. These findings align with those presented in the main results section. This specification curve confirms that the main result is robust under different data construction methods.



Figure 13. Specification curves for deal-by-month level regression. This graph demonstrates the robustness of the regression results across various specifications: (1) Regression Type: Incorporating either pair FE, VC city by month FE and startup city by month FE, or just pair FE and VC city by month FE. (2) IV Measure: Using only the number of weekend passersby or also including passersby during non-working hours on weekdays. (3) Employee Device Criteria: Defining a device as an employee device if it's detected around the VC building for either 15 or 20 working days in a given month. (4) Duration of Stay: Considering stays of 1, 10, 30, or 60 minutes as valid VC monitoring activities. In total, 32 different methods to construct the dependent and instrumental variables were employed. A red point signifies a coefficient that is statistically significant, as evidenced by first-stage F-statistics exceeding 10. Blue bars represent the 95% confidence interval with clustered standard errors. The gray area in the bottom panel specifies the exact specification for each coefficient.

In Section A of the Internet Appendix, I provide the specification curves for Section 5.2, where the dependent variable is the CEO experience. The specification curve exhibits robustness and consistency that are similar to those of the main results.

5.3.2 Alternative Regression Models

In this section, I examine the robustness of the regression results by employing two alternate regression models: deal-level regression and VC by month-level regression. It's reasonable to consider alternative regression models since there isn't a singular, standard regression model best suited for the specific research question in this paper, which investigates how increased monitoring on a current deal can potentially enhance the VC's future deals' performance.

The first alternative method is deal-level regression. I aggregate the average monthly intensity during the first 12 months, and treat it as a monitoring measure for the deal, subsequently testing its impact on future deals. Essentially, this approach condenses the deal by month level information into deal-level. Both the independent variable (#meetings) and the instrumental variable (#passersby) are collapsed similarly to maintain the same intuition. Specifically, the first stage regression is:

$$Monitoring_{ij} = \alpha_0 + \alpha_1 Passersby_{ij} + \alpha_i + \alpha_t + distance_{ij} + \eta_{ij}$$
(3)

where *i* indexes VC firms, *j* indexes portfolio companies, and *t* indexes months. Monitoring represents the monthly meeting times between the VC and the portfolio company. α_i represents VC fixed effects, while α_t accounts for month fixed effects. η_{ij} is the error term.

The second stage regression is:

$$y_{i,t+12} = \beta_0 + \beta_1 Monitoring_{ij} + \alpha_i + \alpha_t + distance_{ij} + \epsilon_{ij}$$
(4)

In this case, $Monitoring_{ij}$ is the fitted value of the monitoring measure from the firststage regression. $y_{i,t+12}$ is the dependent variable of interest, capturing the quality of the subsequent portfolio companies that the VC associates with within a 12-month timeframe following the monitoring activities.

The key advantage of the deal-level regression lies in its intuitive nature, as both the dependent and independent variables represent deal-specific characteristics. However, its drawback is the difficulty in controlling for local shocks, since the variation is now on the deal level and not the deal-by-month level. This makes it harder to incorporate additional location by month level variables to control for local shocks. In the Internet Appendix Section B, I plot the specification curves, with the dependent variable being the future deal's CEO experience from 12 to 24 months post the current deal. The specification curve demonstrates that the majority of the coefficients have a similar sign and magnitude to the main regression, confirming the robustness of the main results under the deal level regression.

The second method is the VC by month-level regression. Here, detailed data are aggregated at the VC by month level. In any given month, a VC might visit several portfolio companies. I use the total number of these meetings as the independent variable, and I collapse the instrumental variable in a similar way. Specifically, the first stage regression is:

$$Monitoring_{it} = \alpha_0 + \alpha_1 Passersby_{it} + \alpha_i + \alpha_t + \alpha_{city(i)} \times \alpha_t + \eta_{ij}$$
(5)

The second stage regression is:

$$y_{i,t+12} = \beta_0 + \beta_1 Monitoring_{it} + \alpha_i + \alpha_t + \alpha_{city(i)} \times \alpha_t + \epsilon_{ij}$$
(6)

This regression model, when compared to the deal by month level main regression, aligns more closely with a standard panel data regression since the data now offer a panel view of VC's monitoring behavior and subsequent performance. However, the drawback is the less intuitive nature of the instrumental variable. Initially, the IV measured the number of passersby traveling between the VC and a specific portfolio company. Now, with aggregation at the VC by month level, the IV captures the number of passersby traveling between the VC building and all portfolio companies' buildings. This modification compromises the original intuition and may result in a weak instrument problem. The Internet Appendix displays the specification curve for the VC by month level regression. While there are some significant results, the signs are not consistent.

In conclusion, the regression results are robust under the deal-level regression but do not consistently hold in the VC by month-level regression. The lack of consistency in the VC by month-level regression may be attributed to the fact that, in this level of analysis, the proposed instrumental variable loses its economic intuition. This, in turn, might result in weak instrument problems, leading to potential bias and inefficiency in the regression estimates.

5.3.3 Alternative Outcome Variables

Finally, I examine the robustness of the results with respect to alternative selections for the dependent and independent variables, as well as the timespan. Figures in the Internet Appendix Section C illustrate the specification curves for these different choices.

The dependent variable in this scenario is the Mosaic Score, a product of CB Insights, which is a composite measure that assesses a startup's health and its potential for future success. This score encompasses four distinct models, referred to as the 4Ms - Momentum, Market, Money, and Management. Measured on a 1000-point scale, with 1000 representing the best score, it serves as an alternative outcome variable, providing a substitute for the IPO rate.

The independent variable under consideration is the total number of meetings between the VC and the startup. These graphs demonstrate the regression results over varying timespans: 0 to 24 months, 6 to 24 months, and 12 to 24 months.

Across these three scenarios, I examine over 750 different specifications. Notably, the vast majority exhibit the same sign and significance as the main regression. These analyses confirm the robustness of the results when considering alternative selections for the dependent variable, independent variable, and timespan.

6. Conclusion

This paper explores the relationship between venture capitalist (VC) monitoring activities and their subsequent investment performance. I use a new method to analyze cell phone signals around VC and portfolio company office buildings, and recover the frequency of monthly meetings from the data. I use the volume of passersby traveling between the VC and startup locations during the weekend as an IV for the monitoring activity. The regression results provide strong evidence supporting the hypothesis that increased VC monitoring is beneficial in securing subsequent deals of higher quality. This positive impact was apparent across various performance measures, such as the experience of the CEO and the chance of the company becoming a unicorn. Future research could explore the dynamics of VC monitoring in greater depth, particularly the mechanisms through which monitoring impacts VC performance.

In conclusion, this paper brings a new perspective on the causal relationship between VC monitoring activities and their investment performance. The results illustrate the significant role of monitoring in the venture capital process and provide a basis for further exploration into this critical aspect of the VC industry.

Appendix



A Case Study in San Francisco

Figure 14. 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 15. 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 16. 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 when haze or smoke was reported. Data source: https://weatherspark.com/.

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