How do Venture Capitalists become Influential?

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January 2025

Abstract

This study investigates how venture capital firms strategically ascend from peripheral to core positions within investment networks. Using comprehensive US VC investment data from 2010-2021, I employ k-shell decomposition and dynamic network analysis to track changes in investors' positions. Through Granular Instrumental Variables and Triple Difference analyses, I examine three paths to the core: co-investing with influential VCs, backing their investments, and having one's investments backed by them. The results show that the third path provides the strongest boost to influence and financial success, regardless of the result of the connecting company, suggesting that the validation of the network of prominent VCs carries more weight than performance alone.

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1 Introduction

In venture capital, who you know can matter as much as what you know. Well-connected VCs consistently outperform their peers, achieving triple the successful exit rates of peripheral investors. Yet while the correlation between network centrality and performance is well-established Hochberg et al. [2007], we know surprisingly little about how peripheral investors can strategically ascend to more central and influential positions within these networks. This gap in understanding creates inefficiencies in the VC market, potentially limiting competition and innovation by making it harder for emerging funds to establish themselves. Indeed, the venture capital (VC) industry plays a pivotal role in fostering innovation, economic growth, and technological advancement by providing crucial funding and support to promising startups.

This research builds on [Nahata, 2008] findings that reputation in venture capital markets significantly impacts investment performance and exit outcomes. While Nahata focused on lead VC reputation, I extend this analysis to examine how network position and influence evolve through different types of connections. In recent years, the importance of network position in determining VC firm success has gained considerable attention from researchers and practitioners alike. Studies have shown that well-connected VCs tend to outperform their less-connected counterparts in terms of investment returns, portfolio company performance, and overall fund success [Hochberg et al., 2007, Sorenson and Stuart, 2001].

The importance of studying network dynamics is further underscored by [Ewens et al., 2021] who show that changes in the VC ecosystem, particularly the rise of accelerators and platforms, have fundamentally altered how entrepreneurs and investors connect. My analysis of network formation complements their work by examining how these connections translate into influence. However, while the correlation between network centrality and performance has been well-established, the specific mechanisms through which peripheral investors can ascend to more central and influential positions within these networks remain largely unexplored.

My study aims to address this gap in the literature by investigating three fundamental questions about the dynamics of influence in venture capital networks. First, I examine through what specific mechanisms peripheral venture capital firms can ascend to more central network positions, focusing on three potential paths: direct co-investment with influential VCs, providing follow-on funding to companies backed by influential VCs, and having one's portfolio companies receive follow-on funding from influential VCs. Second, I analyze how the effectiveness of these paths varies based on the timing of the connection (early vs. late stage investments), the relative network positions of the connecting VCs, and the ultimate success of the connecting investment. Third, I investigate to what extent improvements in network position are causally driven by connections with influential VCs, rather than reflecting unobserved VC quality or strategic anticipation of future influence.

To achieve this objective, I employ a novel methodological approach that combines k-shell decomposition analysis with a dynamic network model. The k-shell decomposition technique was developed to stratify a network and clearly divide the core (center) from the periphery: high shell could have low degree centrality, and high degree can be in low shell. It has been proved to quantify nodes influence Kitsak et al. [2010]. It was recently introduced to the study of VC networks by Li et al. [2023], as it provides a more nuanced measure of an investor's position within the network structure compared to traditional centrality measures. This approach offers advantages over traditional centrality measures by capturing not just the quantity of connections but also their strategic value within the broader network structure, providing a more nuanced measure of influence that better reflects how information and opportunities flow through VC networks.

After having confirmed causal relationships between network influence and performance (found by Li et al. [2023]), I construct a temporal syndication network of US VC institutions, analyzing it month by month to track changes in investors' positions over time. This dynamic approach enables me to capture complex temporal patterns in VC investment activities, including burstiness, memory effects, and non-stationarity, which are often overlooked in static network analyses.

Further, I incorporate the type of connection among VCs as an additional dimension. This allows me to examine whether the effect of moving to a central position differs for how the connection happened, providing a more nuanced understanding of how network effects vary across link types. I identify and examine three distinct paths through which peripheral investors can connect to more central network positioned VCs:

1. Syndication (co-investing) with influential VCs: This involves a peripheral investor participating in a syndicated investment alongside a more established, core investor.

2. Backing investments of influential VCs: In this scenario, a peripheral investor provides follow-on funding to a company already backed by a core VC.

3. Having their own investments backed by influential VCs: This occurs when a company in the peripheral VC's portfolio receives later-stage funding from a core VC.

To establish causal relationships between connections among investors and influence changes, I employ a Granular Instrumental Variables (GIV) approach. This method, inspired by Gabaix and Koijen (2024), is particularly well-suited to this context because it exploits idiosyncratic variations in connection opportunities that arise from the complex, multi-party nature of VC deals - variations that are plausibly exogenous to both VCs' existing network positions and their unobserved characteristics. I construct granular instruments for each VC firm, capturing the sum of connections to influential

VCs made in early, late, and same-stage investment rounds. Each connection is weighted by the difference between the actual connection and the expected number of connections, given the VC firm's characteristics. This GIV approach offers several advantages: it allows me to estimate the direct effects of different types of connections on network position, helps mitigate endogeneity concerns by focusing on idiosyncratic variation, and enables the exploration of heterogeneous effects across firm characteristics. The results from this analysis, which rely on demeaned instruments, provide evidence for the causal impact of connections to influential VCs on a firm's network position, with early-stage connections emerging as particularly crucial for improving network centrality.

Further, to enter into the details of each connection, I employ a triple difference (DDD) analyses. The technique complements the previous approaches by leveraging the temporal sequence of connections and the relative positions of connecting VCs, allowing me to isolate the causal effect of forming connections with influential VCs from other confounding factors such as underlying VC quality or market conditions. Further, the DDD approach allows me to estimate the causal effect of moving to a more central network position on a VC firm's performance by comparing the change in performance for VC firms that connect to another VC firm in a high central position (the treatment group) with the change in performance for firms that do not (the control group). I define the treatment as the connection with a VC positioned in a shell with a high k-core value, specifically a link between a more peripheral k-shell VC to a more central k-shell VC. The three dimensions considered are the connection type, the influence of the connected investor, and the difference in k-shell between the two investors, which expand to a further one when including the success of the connecting company.

My findings reveal that the third path - having one's investments backed by influential VCs - has the most significant impact on a peripheral VC's rise to influence, regardless of the eventual success of the connecting company. This suggests that the act of having a core VC validate a peripheral VC's investment choice carries more weight in the network than the ultimate financial performance of that investment.

To formalize these mechanisms, I develop a theoretical model of influence accumulation in venture capital networks. The model shows how different types of connections contribute asymmetrically to a VC's influence, with early-stage validation from prominent VCs providing disproportionate returns. The dynamic framework demonstrates how initial advantages in network position can create persistent differences in performance through both state dependence and path dependence. By modeling VCs' optimal connection strategies, the theory explains why VC networks exhibit core-periphery structure and generates testable predictions about how influence accumulates based on connection timing and partner characteristics. This theoretical foundation advances our understanding of how network position creates economic value, bridging the gap between empirical observations of network centrality's importance and the underlying mechanisms through which network position affects venture capital performance.

These results have significant implications for the understanding of the VC industry and offer actionable insights for both emerging and established VC firms. They suggest that careful relationship curation and the ability to attract follow-on investments from core VCs may be more crucial for gaining influence than simply achieving a high success rate in exits, particularly for early-stage investors.

My research contributes to several key branches of literature in entrepreneurial finance and network theory. Firstly, it extends the literature on VC network centrality and performance (Hochberg et al. [2007], Sorenson and Stuart [2001]) by providing causal evidence for the impact of network position on VC firm success. By employing GIV and DDD analysis, I move beyond correlational findings in an effort to establish a causal relationship between network influence and performance outcomes. Secondly, it contributes to the growing body of work on dynamic network analysis in financial markets (Di Maggio et al. [2019]) by introducing a temporal dimension to the study of VC networks. My dynamic network model captures complex temporal patterns that are often overlooked in static network analyses, providing a more accurate representation of the evolving VC ecosystem. Thirdly, it advances the literature on k-shell decomposition in complex networks (Kitsak et al. [2010], Li et al. [2023]) by applying this technique to VC syndication networks. This approach offers a more nuanced measure of centrality that captures the quality and embeddedness of network connections, not just their quantity. Lastly, it contributes to the broader literature on the mechanisms of influence and success in entrepreneurial ecosystems (Hsu [2004], Bygrave [1987]) by identifying specific pathways through which peripheral players can gain centrality and influence. This provides valuable insights into the social and reputational dynamics that underpin success in the VC industry.

The remainder of this paper is structured as follows: Section 2 provides a comprehensive review of the relevant literature, highlighting the key gaps that my research aims to address. Section 3 describes the data and methodology employed in this study, including the construction of the dynamic network and the k-shell decomposition technique. Section 4 presents the results of my analyses, including the GIV model and the DDD model. Section 5 discusses the implications of these findings for various stakeholders in the VC ecosystem and situates them within the broader context of entrepreneurial finance research. Finally, Section 6 concludes with a summary of the key contributions, limitations of the study, and suggestions for future research directions.

By providing a comprehensive analysis of the dynamics of influence and success in venture capital networks, this study not only advances the theoretical understanding of VC ecosystems but also offers practical insights for investors, entrepreneurs, and policymakers navigating the complex landscape of entrepreneurial finance.

2 Literature Review

The intricate web of relationships within the venture capital industry has long fascinated researchers, with network centrality emerging as a crucial factor in understanding VC performance. Hochberg et al. [2007] laid the groundwork for this field of study with their seminal work, revealing a strong correlation between a VC firm's network position and its investment success. Their findings painted a clear picture: better-connected VCs were significantly more likely to see their portfolio companies through to successful exits.

This revelation sparked a novel line of research, with scholars delving deeper into the nuances of VC networks. Hochberg et al. [2010] took the next logical step, examining how these networks shape the competitive landscape. They uncovered an intriguing dynamic: densely networked markets act as formidable barriers to entry, presenting a challenge for newcomers while entrenching the position of well-connected incumbents. This insight shed light on the strategic importance of network building in the VC world, not just for performance but for market positioning as well.

As researchers peeled back the layers of VC networks, the phenomenon of syndication emerged as a key area of interest. Lerner [1994] observed a fascinating pattern in how VCs choose their co-investment partners. Established firms, he noted, tend to stick together in early funding rounds, like exclusive members of a private club. However, as investments progress to later stages, these same firms become more willing to bring less established players into the fold. This dance of reputation and risk-sharing hints at the complex social dynamics at play in the VC ecosystem. Further, [Nahata, 2019] provides evidence that VC reputation affects syndicate formation and structure. More reputable VCs are more selective in their syndicate partners and tend to maintain smaller, more closely-knit syndicates.

The geographical implications of these networks didn't escape notice either. Sorenson and Stuart [2001] illuminated how syndication networks serve as bridges across physical distances. Their work revealed that well-connected VCs could confidently venture into unfamiliar territories, relying on the local expertise of their syndicate partners. This finding underscored the power of networks in expanding a VC's reach and influence beyond their home turf.

The question of what drives network formation also came under scrutiny. Gu et al. [2019] challenged conventional wisdom by suggesting that structural embeddedness, rather than relational ties, plays a more significant role in shaping VC networks. This insight shifted the focus from personal relationships to shared interests and complementary resources as the building blocks of effective syndication networks.

Bellavitis et al. [2017] added another layer of complexity to the understanding, demonstrating that the benefits of network position are not uniform across all VC firms. They found that a firm's resource endowment can modulate the advantages gained from network centrality, highlighting that in the VC world, as in many others, context matters. The fragility of these networks also came to light through the work of Zhelyazkov and Gulati [2016], who examined the aftermath of syndication breakups. Their research revealed the long shadow cast by failed partnerships, highlighting the importance of reputation and reliability in maintaining a strong network position.

While degree centrality has been the primary measure of network position in most VC network studies, recent work in network science has shown the promise of k-shell decomposition for identifying influential nodes in complex networks. Kitsak et al. [2010] demonstrated that a node's k-shell value is a better predictor of its influence in spreading processes than simply its degree. Indeed, in the context of VC networks, Li et al. [2023] applied k-shell decomposition to analyze the evolution of syndication networks in the Chinese VC market. Their work not only reinforced the link between network position and performance but also revealed distinct groups of VCs with varying growth trajectories and success rates. This approach opened new avenues for understanding the stratification within the VC community.

Recent studies have further illuminated the nuanced role of networks in venture capital, particularly focusing on alumni connections and gender dynamics. Garfinkel et al. [2024] delved into the impact of alumni networks on venture capital financing, revealing how shared educational backgrounds can influence investment decisions and outcomes. Complementing this, Howell and Nanda [2023] brought attention to the gendered aspects of networking in VC. Their research demonstrated that increased exposure to investors can have differential effects based on gender, highlighting how networking frictions in venture capital may not be uniformly experienced or resolved. These studies collectively emphasize the multifaceted nature of VC networks, showing that both institutional affiliations and personal characteristics play crucial roles in determining network efficacy and investment outcomes.

Most studies of VC networks have relied on static network representations. However, recent work has highlighted the importance of considering the dynamic nature of these networks. Zava and Caselli [2024] developed a dynamic bipartite network model to capture complex temporal patterns in VC investment activities. Their model accounts for burstiness in investment events, memory effects in network formation, and nonstationarity across different funding stages.

Nevertheless, despite these significant advancements, several important questions remain unanswered. In fact, the specific mechanisms through which peripheral investors can gain centrality and influence in VC networks have not been thoroughly explored. Furthermore, the relative importance of different paths to gaining influence, such as syndicating versus receiving follow-up investments, has not yet been quantified. Furthermore, the relationship between an investor's evolving network position and their ability to attract follow-on investments for portfolio companies warrants a closer examination.

Lastly, how the position of the network impacts investment performance at different stages of the startup lifecycle - from early stage investments to later stage - requires further investigation.

These gaps in current knowledge underscore the complexity of VC networks and highlight promising avenues for future research. Addressing these questions will not only enhance theoretical understanding but also provide practical insights for both established and emerging players in the venture capital ecosystem. The purpose of my study is to address these gaps by combining the k-shell decomposition analysis with a dynamic network model. By doing so, I seek to provide a more comprehensive understanding of how influence is gained and maintained in VC networks, and how this relates to investment performance across different stages of the startup lifecycle.

3 Economic Contribution

This paper contributes to the literature on network formation and industry dynamics by developing a theoretical model that explains how venture capitalists gain and maintain influence through their network position. While previous research has established correlations between network centrality and performance, the mechanisms through which network position creates economic value have remained largely unexplored.

The model provides a novel framework for understanding how k-shell position affects a VC's ability to extract economic rents. The value function takes the form:

$$\pi_{it} = P(Success_{it}|k_{it})R - c(k_{it}) \tag{1}$$

where higher k-shell positions increase success probability but face convex costs. This formalization helps explain why certain network positions persistently generate higher returns.

A key innovation is the introduction of asymmetric returns to different types of connections:

$$\frac{\partial I_{it}}{\partial e_{it}} \neq \frac{\partial I_{it}}{\partial l_{it}} \neq \frac{\partial I_{it}}{\partial s_{it}} \tag{2}$$

This extends classic network formation models by demonstrating how the timing and sequencing of connections fundamentally affects their value. The model shows that early connections to influential VCs provide disproportionate returns.

The dynamic nature of influence accumulation is captured through:

$$k_{it} = k_{i,t-1} + \beta_e e_{it} + \beta_l l_{it} + \beta_s s_{it} + \gamma \bar{k}_{-i,t-1} + \epsilon_{it} \tag{3}$$

This advances our understanding of industry dynamics by formalizing how early advantages in network position can create persistent performance differences. The model demonstrates that network position exhibits both state dependence and path dependence.

The equilibrium predictions about network structure emerge from VCs' optimal connection strategies:

$$e^*_{it} = f(k_{i,t-1}, B_{it}, \mathbf{X}_{it}) \tag{4}$$

This provides theoretical foundations for understanding why VC networks exhibit core-periphery structure and helps explain empirical patterns in network formation. The model shows how heterogeneity in VC characteristics leads to systematic differences in connection strategies.

The welfare implications of network formation can be analyzed through:

$$W = \sum_i \pi_{it} - \sum_i c(k_{it}) \tag{5}$$

This enables evaluation of policies to improve market outcomes by affecting network formation costs or benefits. The model suggests that reducing connection costs for peripheral VCs could enhance market efficiency.

By formalizing these mechanisms, the model advances our understanding of how network position creates economic value, why timing matters in network formation, how influence accumulates dynamically, what determines equilibrium network structure, and how network effects impact market efficiency. These insights provide a theoretical foundation for understanding the role of networks in venture capital while generating novel testable predictions that I validate in the empirical analysis.

4 Methodology

The paper employs several complementary analytical approaches to understand how venture capitalists become influential, each serving a crucial purpose in establishing robust and comprehensive findings. We first construct a dynamic co-investment network, able to capture burstiness, memory, and investors' behaviors across time. At the foundation of my analysis lies the k-shell decomposition methodology, which provides a sophisticated way to measure a VC's position in the network beyond simple connection counting. This approach captures not just how many connections a VC has, but how strategically positioned those connections are, helping identify truly influential VCs versus those who simply have many connections.

The Granular Instrumental Variables (GIV) analysis addresses the critical challenge of causality: Do connections make VCs influential, or do influential VCs simply attract more connections? By using unexpected connections between VCs as a natural experiment, this approach helps prove that forming certain types of connections actually causes changes in network position. Importantly, the GIV analysis reveals that having your investments backed by influential VCs is particularly important for gaining influence in the VC network.

The Triple Difference (DDD) analysis examines how three key factors interact to affect a VC's rise to influence: the type of connection (early, late, or same-stage investment), the initial difference in network positions between connecting VCs, and whether the connection is with an influential VC. This analysis can observe each connection singularly, thus enjoy the advantages of granularity (as timing, consequentiality, and characteristics of the connected investor). It confirms that having your investments backed by influential VCs is the most effective path to gaining influence, and it inserts nuances relative to the difference in influence among VCs and the company connecting the two, demonstrating how timing and partner choice matter in network building, but the connecting company does not.

To ensure the robustness of my findings, I conduct several critical checks. Through analyzing anticipatory connections, I prove that the results are not driven by VCs connecting with others they expect to become influential. By examining indirect connections, I show that the findings hold even when looking at connections formed through intermediaries. The high-potential investors analysis demonstrates that the results are not just capturing high-quality VCs naturally attracting more connections.

The combination of these analytical approaches proves useful in multiple ways. First, they work towards establishing causality, demonstrating that certain types of connections actually cause VCs to become more influential, moving beyond mere correlations. Second, I provide practical guidance by identifying specific strategies VCs can use to build influence, particularly highlighting the value of early-stage investments that attract follow-on funding from influential VCs. Third, I challenge conventional wisdom by showing that who backs your investments matters more than who you co-invest with. The proposed comprehensive approach also delivers robust findings that hold up across multiple analytical methods and various robustness checks.

4.1 Data

My study utilizes a comprehensive dataset of US-based venture capital investments from 2010 to 2021. I collected the data from the academic Crunchbase.com Web API, which is widely regarded as the world's most comprehensive open dataset about startup companies. Crunchbase was founded in 2007 by TechCrunch as a way to easily track startups in the news. The data is manually recorded and managed by various contributors affiliated with the Crunchbase platform, including incubators, venture funds, and individuals. Additionally, web crawlers enrich the data daily by searching for news about IPOs, acquisitions, and funding rounds, which are then verified by the platform's data analysts.

I focused my data collection on startups founded across the globe between 2010 and 2017 that received at least one round of funding from an US-based investor. For each organization, I gathered additional information such as foundation dates, headquarters locations, industry classifications, estimated revenue ranges, number of employees, funding rounds, acquisitions, and IPOs. I meticulously collected all deals these companies raised between 2010 and 2021, identifying all financial organizations and angel investors involved in each round, along with the general partners responsible for the deal. I also gathered information on the amount raised and the funding stage for each round.

For the investors, whether they were angel funds, accelerators, or VC firms, I collected data on their founding date, number of investments made, companies in their portfolio, investments led, IPOs, and acquisitions. I also gathered more general information such as stage of expertise, description, and headquarter location. For angel investors and individual investors, I additionally collected information on gender, job titles in current and previous positions, social media accounts, and educational background. All the information is made available in different sections in Crunchbase.

To ensure data quality and reliability, I implemented a rigorous cleaning process. I removed inconsistencies such as funding rounds registered prior to a company's foundation date, retaining only the most reliable information based on Crunchbase's trust code value. I adopted a strong self-penalizing data cleaning strategy to strengthen the validity of my results.

The dataset includes key variables such as VC firm identifiers, portfolio company identifiers, investment dates, investment amounts, investment rounds (e.g., seed, Series A, Series B), exit events (IPOs, acquisitions), and industry sectors. I focused on VC firms that made at least 5 investments during this period to ensure a meaningful analysis of network position and evolution.

The main statistics are available in Table 1, offering an overview of VCs firms' characteristics and Investment stage distribution, and in Table 2 and Table 3, that focus on portfolio companies' distribution across geographies and industries. Differently, Table 4 articulates the data cleaning process and the several samples construction. Further, a detailed description of data and variables is outlined in the appendix.

Table 1: Summary Statistics of VC Firms and Investments

Variable	N	Mean	SD	Min	Max
Panel A: VC Firm Characteristics					
Number of Investments	17,436	174.76	285.32	5	1,245
Number of Lead Investments	17,436	66.99	112.45	0	528
Number of IPO Exits	17,436	69.60	98.76	0	412
Firm Age (years)	17,436	12.45	8.67	1	45
K-shell Value	17,436	122.84	115.62	1	365
Panel B: Investment Round Distribution					
Angel/Pre-Seed	155,484		3.5%		
Seed	1,456,400		32.7%		
Series A	1,557,120		35.0%		
Series B	1,369,530		30.8%		

Table 2: Geographic Distribution of Portfolio Companies

Location	Number of Deals	% of Total Investments
California (excl. SF)	865,796	19.5%
San Francisco	1,594,830	35.9%
US (excl. California)	1,901,500	42.8%
Rest of World	68,264	1.8%
Total	4,430,390	100%

Table 3: Industry Distribution of Portfolio Companies

Industry Group	Number of Deals	Percentage
Finance, Business Services	946,476	24.0%
Consumer, Retail	873,044	22.1%
Media, Arts	616,258	15.6%
Software	546,004	13.8%
Technology	513,420	13.0%
Healthcare, Energy	451,164	11.5%
Total	3,946,366	100%

Table 4: Data Cleaning Process and Sample Construction

Step	Observations	Remaining (%)
Panel A: Initial Data Collection		
Raw data from Crunchbase (2010-2021)	4,500,000	100.0%
Panel B: Removal Steps		
Remove inconsistent funding dates	-186,238	95.9%
Remove pre-foundation investments	-95,459	93.8%
Remove unreliable trust codes	-152,346	90.4%
Remove missing investor information	-125,012	87.6%
Remove investors with <5 investments	-136,975	84.6%
Panel C: Sample Restrictions		
Require complete company information	-255,016	78.9%
Panel D: Final Sample Composition		
Total dyadic connections	3,803,954	–
Number of unique VCs	17,436	–
Number of unique portfolio companies	42,568	–
Number of investment rounds	65,892	–
Connections involving influential VCs	1,164,917	30.6%

Note: This table presents the step-by-step data cleaning process. Panel A shows the initial raw data. Panel B details the removal of problematic observations. Panel C shows additional sample restrictions. Panel D presents the final sample composition.

4.2 Network Construction

I construct a dynamic network based on the investment relationships between VC firms, connected by an investment in the same company. This network grows in a discrete fashion from 2010 to 2021, with funding interactions and new nodes inserted at the beginning of every month, creating a sequence of graph snapshots. The nodes are the investors and the links represent the companies in which they both invested. The approach to measuring network evolution builds on methodological insights from [Nahata, 2008] regarding the dynamic nature of VC reputation and influence. However, while Nahata focuses on IPO market share as a measure of reputation, I employ k-shell decomposition to capture more nuanced aspects of network centrality.

I update the network at monthly intervals, allowing me to capture complex temporal patterns not evident in static networks, such as burstiness, memory effects, and non-stationarity. Burstiness refers to the tendency of nodes or edges to appear in bursts over time, which I observe in the uneven deal flow across the 12 years studied. Memory effects are captured by considering how past states influence future network formations, which is crucial in determining who attracts and follows whom in the VC ecosystem. Non-stationarity is addressed by allowing the network structure to change over time, particularly important when analyzing transitions between funding stages.

This dynamic network model allows me to explicitly capture complex temporal patterns and has the potential to significantly enhance the understanding of the dynamics underlying early-stage funding in the venture capital ecosystem.

4.3 K-shell Decomposition

To measure the centrality and influence of VC firms within the network, I employ k-shell decomposition. This method provides a more nuanced measure of a node's centrality compared to simple degree centrality, as it takes into account the overall connectivity of the node's neighbors.

The k-shell decomposition process is as follows:

1. Start with $k = 1$
2. Remove all nodes with degree less than or equal to k
3. Recalculate degrees for remaining nodes
4. Repeat steps 2-3 until no nodes can be removed
5. Assign k-shell value k to all removed nodes
6. Increment k and repeat the process until all nodes are assigned a k-shell value

I perform k-shell decomposition on each monthly snapshot of the network, allowing me to track changes in VC firms' k-shell values over time.

To better understand the k-shell decomposition process, I provide the example displayed in Figure 1. The k-shell decomposition process, as described above, is visually represented in the accompanying figure. The figure illustrates a simple network's structure, segmented into three distinct shells corresponding to k=1, k=2, and k=3. In each shell, the degree is k or more. Specifically, the yellow nodes have a degree of one, the green nodes have a degree of two, and the purple nodes have a degree of three.

In the initial steps of the decomposition process, nodes in the k=1 shell are removed. This includes nodes such as No.1 and No.2, which are eliminated in the first iteration. Following these removals, node No.3, which initially had more than one connection, now only has one remaining connection and is therefore removed in the subsequent step. By contrast, node No.4 is not eliminated in the first round because, despite the removal of its neighbouring nodes with a degree centrality of 1 (No.1, No.2, and No.3), node No.4 maintains two connections and thus belongs within the k=2 shell. In a subsequent step, all nodes with two or fewer connections are progressively removed and assigned the k-shell number 2. This process continues until all nodes are assigned a k-shell value.

Nodes can have the same degree centrality but belong to different shells. This is exemplified by nodes No.5 and No.6, as shown in the figure. Despite both having a degree centrality of 7, node No.5 resides in the k=1 shell, whereas node No.6 is part of the k=3 shell. When all nodes with a degree centrality of 1 connected to node No.5 are removed, node No.5 becomes isolated and is subsequently eliminated, placing it in the k=1 shell. In contrast, node No.6 retains three stable connections even after the removal of all nodes with a degree centrality of 1 and 2. Only upon the removal of nodes with a degree centrality of 3 is node No.6 eliminated, thereby assigning it to the 3-shell (k=3 shell). This process highlights how the k-shell decomposition goes beyond degree centrality, capturing the importance of a node's position within the network.

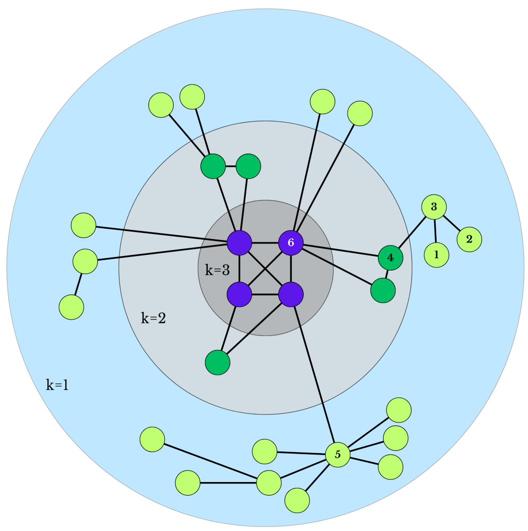

Figure 1: **K-shell decomposition of a network.** Nodes are assigned to shells (k=1 yellow, k=2 green, k=3 purple) based on their connectivity. The process removes nodes iteratively, starting with the least connected. Nodes 5 and 6 illustrate how same-degree nodes can belong to different shells, demonstrating that k-shell decomposition captures network position importance beyond simple degree centrality.

4.4 Path Analysis

To investigate how peripheral investors can move to more central positions, I define and analyze three potential paths based on the concept of k-shell decomposition in syndicated investment networks. This approach provides a nuanced measure of an investor's position within the network structure, building upon previous work that linked degree centrality to investor success.

The first path I examine is co-investment, where a peripheral investor participates in a syndicated investment alongside a more established, core investor.

The second path I analyze is backing an investment of an influential VC. In this scenario, a peripheral investor provides follow-on funding to a company already backed by a core VC.

The third path I investigate is having one of the peripheral VC's investments backed by an influential VC. This scenario, where a company in the peripheral VC's portfolio receives later-stage funding from a core VC, emerges as the most effective path to gaining influence in my analysis.

For each VC firm in my dataset, I meticulously track instances of these events and analyze their impact on the firm's subsequent k-shell position. I construct a temporal syndication network of US VC institutions, analyzing it month by month to track changes in investors' positions.

By examining these three paths and their relative effectiveness, I aim to provide insights into the dynamics of influence and centrality in the venture capital ecosystem. This analysis offers guidance for emerging VC firms seeking to establish themselves in competitive markets, potentially serving as a foundation for developing new investment strategies that quantitatively incorporate both financial and social components.

4.5 K-shell and success

To test my hypotheses and quantify the relationships between network position, funding attraction, and investment performance, I employ several statistical techniques. First, I employ a panel regression analysis to examine the relationship between k-shell position, and investment performance metrics (exit rates, follow-on funding success, unicorn creation). Results are displayed in Table 5 and confirm that the mechanism that Li et al. [2023] found for the Chinese market applies also to the US scenario. Indeed, k-shell position and success are positively correlated and the latter follows the former.

But, the paper is centered on the applications of both the Granular Instrumental Variables Approach and the Triple Differences analysis to assess the causal impact of moving to a more central network position on subsequent investment performance. By combining these methodological approaches, I aim to provide a comprehensive and robust analysis of the dynamics of influence and success in venture capital networks.

4.6 GIV: Granular Instrumental Variables Approach

To estimate the causal effect of connections to influential VCs on a firm's network position, I employ a Granular Instrumental Variables (GIV) approach. This method, inspired by Gabaix and Koijen [2024], allows me to exploit idiosyncratic variation in connections to influential VCs while addressing potential endogeneity concerns.

The key outcome I am interested in is the k-shell value of each VC firm at each time point. This measure serves as the dependent variable, providing a nuanced indicator of a firm's centrality and influence within the VC network. Specifically, I track three types of connections:

1. Syndicating (co-investing) with influential VCs (named: same round): This involves a peripheral investor participating in a syndicated investment alongside a more established, core investor.

2. Backing investments of influential VCs (named: late round): In this scenario, a peripheral investor provides follow-on funding to a company already backed by a core VC.

3. Having their own investments backed by influential VCs (named: early round): This occurs when a company in the peripheral VC's portfolio receives later-stage funding from a core VC.

Our GIV approach proceeds as follows. First, I identify influential VCs as those in the top 10% of k-shell values in the network at any given time t. This dynamic definition allows for changes in influential status over time.

Next, I construct granular instruments for each VC firm i. I create three instruments: G_{early_i}, the sum of connections to influential VCs made in early investment rounds; G_{late_i}, the sum of connections to influential VCs made in late investment rounds; and G_{same_i}, the sum of connections to influential VCs made in same-stage investment rounds. Each connection is weighted by the difference between the actual connection and the expected number of connections, given the VC firm's characteristics:

$$G_{j_i} = \sum (z_{ij} - E[z_{ij}]) \tag{6}$$

where z_{ij} is an indicator for a connection of type j (early, late, or same) to an influential VC, and $E[z_{ij}]$ is the expected number of such connections.

I then directly regress the outcome variable (change in k-shell value) on these granular instruments:

$$\Delta Kshell_i = \alpha + \beta_{early} \cdot G_{early_i} + \beta_{late} \cdot G_{late_i} + \beta_{same} \cdot G_{same_i} + \gamma \cdot X_i + \varepsilon_i \tag{7}$$

where X_i is a vector of investor-specific variables as geographical focus, industry focus and concentration, and stage focus.

To explore how the effects vary with firm size, identified as number of portfolio companies, I interact the granular instruments with firm size:

$$\Delta Kshell_i = \alpha + \beta_j \cdot G\_j_i + \delta_j \cdot (G\_j_i \times Size_i) + \gamma \cdot X_i + \varepsilon_i \tag{8}$$

for $j \in \{early, late, same\}$.

To validate the approach, I conduct a test by constructing an instrument $G_{noninfl_i}$ using connections to non-influential VCs and estimate:

$$\Delta Kshell_i = \alpha + \beta_{noninfl} \cdot G_{noninfl_i} + \gamma \cdot X_i + \varepsilon_i \tag{9}$$

This GIV approach offers several advantages. First, it allows me to estimate the direct effects of different types of connections on network position. Second, by focusing on idiosyncratic variation in connections, it helps mitigate endogeneity concerns. Finally, the granular nature of the instruments enables me to explore heterogeneous effects across firm characteristics.

For our Granular Instrumental Variables (GIV) approach to provide valid causal estimates, we require specific sufficient conditions to hold. Our instrument exploits the idiosyncratic component of connections between VCs, measured as $(z_{ij} - E[z_{ij}])$, where z_{ij} represents the actual connection between VC i and VC j, and $E[z_{ij}]$ represents the expected connection based on observable characteristics.

The key sufficient condition for identification is that this idiosyncratic component must be uncorrelated with both the initial network positions (X_i,

X_j) and unobserved characteristics (B_i, B_j) of the connecting VCs. Formally, we require:

$$\mathrm{Cov}((\mathrm{z}_{ij} - E[z_{ij}]), X_i) = 0$$

$$\mathrm{Cov}((\mathrm{z}_{ij} - E[z_{ij}]), X_j) = 0$$

$$\mathrm{Cov}((\mathrm{z}_{ij} - E[z_{ij}]), B_i) = 0$$

$$\mathrm{Cov}((\mathrm{z}_{ij} - E[z_{ij}]), B_j) = 0$$

This condition is plausibly satisfied in the setting due to several institutional features of the VC market. Unexpected deviations from predicted connection patterns typically arise from factors exogenous to both VCs' network positions and characteristics. These include: (1) deal-specific timing constraints, such as when a portfolio company unexpectedly requires additional capital; (2) external market conditions that affect deal availability; (3) portfolio company preferences for specific investor combinations; and (4) geographic coincidences in deal opportunities. These factors create variation in actual versus expected connections that is plausibly independent of both the VCs' existing network positions and their unobserved characteristics.

The validity of our identification strategy is further supported by the multi-party nature of VC deals, where connection formation is not solely determined by bilateral VC characteristics but is also influenced by portfolio company needs and existing investor requirements. This institutional setting helps ensure that deviations from expected connection patterns are driven by factors outside the direct control or characteristics of the VCs themselves.

Standard errors are clustered at the VC firm level to account for potential serial correlation in the error terms. All specifications include controls for VC firm characteristics and year fixed effects to account for time-varying industry conditions.

4.7 DDD: Triple Interaction Difference-in-Differences Model

Further, the analysis focuses on the individual connections among venture capital firms as the primary unit of observation. These continuous measures allow me to capture not just the overall presence and type of connections, but their frequency, evolution and intensity over time. This approach enables a more nuanced analysis of how different types and levels of connecting activity impact a VC's position within the industry network. I track these firms over time, collecting monthly data throughout the study period from 2010 to 2021. This longitudinal approach allows me to capture the dynamic nature of VC networks and how they evolve over time.

The Triple Difference (DDD) analysis in this study examines how VC firms' network positions change based on three key dimensions. The first dimension is the type of connection ($Connection_{(AB),t}$), which can be early-stage (baseline), late-stage, or same-stage investments, capturing how VCs initially connect with each other. The second dimension is the relative network position ($\Delta Kshell_{(AB),(t-1)}$), measured as the difference in k-shell values between the connecting VCs in the period before their connection, which captures the initial status gap between firms. The third dimension is the influence status of the connected VC ($Influence_{B,(t-1)}$), indicating whether the connected VC is in the top 10% of k-shell values at the time of connection. This three-dimensional approach allows us to disentangle how the impact of forming connections varies based on both the type of connection formed (early vs. late vs. same-stage), the initial network position difference between the connecting VCs, and whether the connection is made with an influential VC. For instance, we can examine whether an early-stage connection with an influential VC has a different effect on a firm's network position when there is a large initial k-shell difference compared to when the firms are similarly positioned in the network.

The main model specification is as follows:

$$\Delta Kshell_{A,(t-1,t)} = \beta_0 + \beta_1(Connection_{(AB),t}) + \tag{10}$$

$$\beta_2(\Delta Kshell_{(AB),(t-1)}) + \beta_3(Influence_{B,(t-1)}) +$$

$$\beta_4(Connection_{(AB),t} * \Delta Kshell_{(AB),(t-1)}) +$$

$$\beta_5(Connection_{(AB),t} * Influence_{B,(t-1)}) +$$

$$\beta_6(Influence_{B,(t-1)} * \Delta Kshell_{(AB),(t-1)}) +$$

$$\beta_7(Connection_{(AB),t} * Influence_{B,(t-1)} * \Delta Kshell_{(AB),(t-1)}) +$$

$$\gamma X_{A_t} + \theta X_{B_t} + \tau_{c_{AB}} + \varepsilon_{it}$$

Where:

- $\Delta Kshell_{A,(t-1,t)}$ is the change in K-shell value for VC firm A from time t-1 to t, representing the change in the firm's network centrality.

- $Influence_{B,(t-1)}$ is a dummy variable indicating whether VC firm B was in the top 10% k-shells values at time t-1. It is the treatment of the DDD model.

- $Connection_{(AB),t}$ is a dummy variable indicating the type of connection (early, late, same round) that occurred between VC firms A and B at time t. It is the additional dimension of the DDD model.

- $\Delta Kshell_{(AB),(t-1)}$ represents the difference in K-shell values between firms A and B in the previous period.

- $X_{A_{i,t}}$ and $X_{B_{i,t}}$ are vectors of control variables for firms A and B, respectively.

- $\tau_{c_{AB}}$ represents fixed effects to control for time-invariant characteristics of the connecting company between firms A and B.

- ε_{it} is the error term.

This model allows me to examine how the effect of a connection event on a VC firm's influence (as measured by changes in K-shell value) varies based on the type of connection, the relative network positions of the firms involved, and the influence of the connected firm. The key components of this model and their significance are as follows.

The main effects, represented by β_1, β_2, and β_3, capture the individual effects of connection events, prior network position differences, and the influence of the connected firm on changes in network centrality. These coefficients provide insights into how each factor independently influences a firm's position within the network.

The two-way interactions, denoted by β_4, β_5, and β_6, offer a more nuanced understanding of the relationships between variables. The interaction term $Connection_{(AB),t} * \Delta Kshell_{AB,(t-1)}$ allows me to examine how the effect of different types of connections varies based on the prior difference in network positions between the two firms. The term $Connection_{(AB),t} * Influence_{B,(t-1)}$ captures how the impact of a connection event differs depending on whether the connected VC firm (B) is influential. Lastly, the interaction $Influence_{B,(t-1)} * \Delta Kshell_{AB,(t-1)}$ examines how the effect of connecting with an influential firm varies based on the prior difference in network positions.

Of particular interest is the triple interaction term, represented by β_7. This coefficient on $Connection_{(AB),t} * Influence_{B,(t-1)} * \Delta Kshell_{AB,(t-1)}$ allows me to understand how the effect of different types of connection events on network centrality changes varies simultaneously with both the prior network position difference and the influence of the connected firm. This three-way interaction provides a nuanced view of the conditions under which network connections are most impactful in enhancing a firm's centrality.

The model also incorporates control variables and fixed effects, represented by γ, θ, and τ. These terms allow me to account for other factors that might influence changes in network centrality, including firm-specific characteristics and time-invariant aspects of the relationship between firms. By controlling for these factors, I can isolate the effects of the variables of interest more precisely.

This comprehensive model enables me to disentangle the complex interplay of factors that contribute to a VC firm's movement within the network, providing valuable insights into the dynamics of influence and centrality in the venture capital ecosystem.

Building upon the previous model, this extended specification incorporates an additional dimension: the success of the connecting company. This allows me to examine how the outcome of the joint investment influences network centrality dynamics. The new variable, $Success_c$, is a binary indicator of whether the connecting company achieved a successful exit through acquisition or public listing. The model is outlined as follows:

$$\Delta Kshell_{A,(t-1,t)} = \beta_0 + \beta_1(Connection_{(AB),t}) + \tag{11}$$

$$\beta_2(\Delta Kshell_{(AB),(t-1)}) + \beta_3(Influence_{B,(t-1)}) + \beta_4(Success_c)$$

$$\beta_5(Connection_{(AB),t} * \Delta Kshell_{(AB),(t-1)}) +$$

$$\beta_6(Connection_{(AB),t} * Influence_{B,(t-1)}) + \beta_7(Influence_{B,(t-1)} * \Delta Kshell_{(AB),(t-1)}) +$$

$$\beta_8(Connection_{(AB),t} * Success_c) + \beta_9(Influence_{B,(t-1)} * (Success_c) +$$

$$\beta_{10}(\Delta Kshell_{(AB),(t-1)} * (Success_c)+$$

$$\beta_{11}(Connection_{AB,t} * Influence_{B,(t-1)} * \Delta Kshell_{AB,(t-1)})+$$

$$\beta_{12}(Connection_{(AB),t} * Influence_{B,(t-1)} * Success_c)+$$

$$\beta_{13}(Connection_{(AB),t} * Success_c * \Delta Kshell_{(AB),(t-1)})+$$

$$\beta_{14}(Success_c * Influence_{B,(t-1)} * \Delta Kshell_{(AB),(t-1)})+$$

$$\beta_1 5(Connection_{(AB),t} * Success_c * Influence_{B,(t-1)} * \Delta Kshell_{(AB),(t-1)})+$$

$$\gamma X_{A_t} + \theta X_{B_t} + \omega_{c_{AB}} + \varepsilon_{it}$$

On top of the previous model, the main effects now include β_4, which captures the direct impact of the connecting company's success on changes in network centrality. This coefficient provides insight into how backing a successful company independently influences a firm's network position.

The model introduces several new two-way interactions (β_8, β_9, and β_{10}) that offer more nuanced insights: $Connection_{(AB),t} * Success_c$ (β_8) examines how the impact of different connection types varies based on the success of the connecting company; $Influence_{B,(t-1)} * Success_c$ (β_9) explores how the effect of connecting with an influential firm differs when the joint investment is successful; $\Delta Kshell_{AB,(t-1)} * Success_c$ (β_{10}) investigates how the impact of prior network position differences changes when the connecting company is successful.

The model also includes additional three-way interactions (β_{12}, β_{13}, and β_{14}) that provide even more granular insights into the complex interplay between connection type, firm influence, network position differences, and investment success. The coefficient β_{12} ($Connection_{(AB),t} * Influence_{B,(t-1)} * Success_c$) captures how the effect of different connection types on network centrality changes varies when connecting with an influential firm and the joint investment is successful. For example, a positive β_{12} would suggest that successful investments with influential firms have a stronger positive impact on centrality, especially for certain types of connections (e.g., early-picked connecting company).

Next, β_{13} ($Connection_{(AB),t} * Success_c * \Delta Kshell_{(AB),(t-1)}$) examines how the impact of different connection types on centrality changes depends on both the success of the investment and the prior difference in network positions. A significant β_{13} might indicate that successful investments have a stronger effect on centrality when there is a larger initial gap in network positions, but this effect varies by connection type. Lastly, β_{14} ($Success_c * Influence_{B,(t-1)} * \Delta Kshell_{(AB),(t-1)}$) explores how the joint effect of investment success and connecting with an influential firm varies based on the prior difference in network positions. A positive β_{14} could suggest that successful investments with influential firms have a more pronounced impact on centrality when there is a larger initial network position gap.

These three-way interactions allow me to uncover nuanced patterns in how various factors combine to affect network centrality. They help reveal conditions under which certain types of connections or successful investments might be particularly impactful, providing insights that simpler models might miss. For instance, I might find that early-stage investments (a type of connection) with influential firms are especially beneficial for centrality when they turn out to be successful, but this effect is most pronounced for firms that start with a large network position gap.

Of particular interest is the four-way interaction term (β_{15}), which allows me to understand how all these factors - connection type, firm influence, prior network position difference, and investment success - simultaneously interact to affect changes in network centrality. This complex interaction provides a comprehensive view of the conditions under which network connections are most impactful in enhancing a firm's centrality, taking into account the success of the joint investment.

The coefficient β_{15} ($Connection_{(AB),t} * Success_c * Influence_{B,(t-1)} * \Delta Kshell_{(AB),(t-1)}$) represents the most nuanced level of analysis in the model. It captures how the effect of different connection types on network centrality changes when the success of the investment, the influence of the connected firm, and the initial difference in network positions are considered all at once. For instance, a positive and significant β_{15} might indicate that syndication (a type of connection) with influential firms are particularly beneficial for improving centrality when the investment is successful and there is a large initial gap in network positions.

This four-way interaction allows me to identify very specific scenarios or conditions that lead to the greatest improvements in network centrality. It might reveal, for example, that the combination of syndicating with a highly influential firm, achieving investment success, and starting from a relatively peripheral position leads to the most substantial gains in network centrality. Such insights can be invaluable for VC firms strategizing their network-building efforts and investment decisions.

Interpreting this coefficient requires careful consideration of all four interacting factors simultaneously, providing the most comprehensive and detailed understanding of the complex dynamics governing VC network evolution. While complex, this level of analysis can offer powerful insights that simpler models might overlook, potentially uncovering key strategies for VC firms aiming to enhance their network positions.

A key methodological difference in this model is the replacement of τ (company fixed effects) with $\omega_{c_{AB}}$, a vector of company-related control variables. This substitution is necessary to make the $Success_c$ variable effective and tractable within the model. By using company-specific controls instead of fixed effects, I can isolate the impact of investment success while still accounting for company-level factors that might influence network dynamics.

This comprehensive model enables me to disentangle the complex interplay of factors that contribute to a VC firm's movement within the network, including the crucial aspect of investment outcomes. It provides valuable insights into how successful investments, in conjunction with other network and firm characteristics, shape the dynamics of influence and centrality in the venture capital ecosystem. The results from this model will offer a more complete picture of how VC firms can strategically position themselves for growth and increased influence, taking into account not just their network activities but also the performance of their joint investments.

The importance of this model in the context of the research on venture capital networks cannot be overstated. By employing a Triple Difference approach, I am able to achieve several key objectives. First, it works towards isolating causal effects, moving beyond correlation to identify causal relationships between network connections, firm characteristics, and changes in network centrality. Second, I account for heterogeneity, allowing for the effect of network connections to vary based on firm characteristics and outcomes, capturing the complex and heterogeneous nature of VC network dynamics. Third, I can examine interaction effects, exploring how different factors combine to influence network centrality and providing a more comprehensive understanding of the mechanisms at play. Fourth, I control for confounding factors through the inclusion of control variables and fixed effects, increasing the robustness of the findings. Lastly, I capture dynamic effects by focusing on changes in K-shell values over time, allowing me to examine how firms' positions evolve within the network.

This methodology represents a significant advancement in the study of venture capital networks. Unlike previous research that has often relied on static measures of network centrality or simpler regression models, the approach allows me to disentangle the complex interplay of factors that contribute to a VC firm's rise to prominence within the industry network. By applying this model to the comprehensive dataset of VC investments and network connections, I aim to provide novel insights into the mechanisms through which VC firms gain influence and improve their network positions. These findings have important implications for both academic understanding of VC network dynamics and practical strategies for firms seeking to enhance their position within the industry.

4.8 Robustness

In order to strengthen the validity of the main findings and address potential concerns about endogeneity, reverse causality, and other confounding factors, I conducted a series of rigorous robustness checks. These additional analyses are designed to provide further evidence for the causal relationships I propose and to rule out alternative explanations for the results. In the following subsections, I detail three key robustness checks: Anticipatory Connections, Indirect Connections, and High-Potential Investors. Each of these approaches tackles specific methodological challenges and offers complementary insights that bolster the credibility of the main analysis. By employing these diverse strategies, I aim to present a comprehensive and convincing case for the causal role of network position in determining VC performance and influence.

4.8.1 Anticipatory Connections

To address potential concerns about reverse causality or anticipation effects in the main analysis, I implemented a robustness check using "anticipatory connections," also referred to as "pre-influence connections." These anticipatory connections are defined as connections that occur just before a VC becomes influential, specifically entering the top 10% of k-shell values in the network.

Our methodology for this robustness check involved several key steps. First, I identified all VCs in the dataset that transitioned into influential status (top 10% of k-shell values) during the study period. For each of these VCs, I then examined their network connections in the three months immediately preceding their transition to influential status. These connections formed the set of anticipatory connections.

I then replicated the DDD analysis using these anticipatory connections in place of the connections with already-influential VCs from the primary model. The underlying logic of this approach is that if the main results are truly driven by the causal effect of connecting with influential VCs, I should observe little to no effect from these anticipatory connections. Conversely, if I find similar effects from anticipatory connections, it would suggest that the main results might be influenced by other factors or by the anticipation of a VC's rising influence.

The model specification for this robustness check mirrors the main model, with the key difference being the definition of influential connections. In the anticipatory model, the $Influence_{B,(t-1)}$ variable is replaced with a dummy variable indicating whether VC B will become influential in the next three months. All other variables and interactions remain the same, allowing for a direct comparison between the main and anticipatory models.

By comparing the results of this anticipatory model to the main model, I can assess whether the effects I observe are truly due to connections with already-influential VCs or if they might be driven by anticipation of future influence or other confounding factors. This comparison provides evidence for the causal interpretation of the main findings and helps rule out alternative explanations based on reverse causality or anticipation effects.

4.8.2 Indirect Connections

To further strengthen the causal claims and address potential endogeneity concerns, I conduct an additional robustness check that exploits the structure of the VC network. Specifically, I examine the effect of indirect connections that occur when two VCs become connected through a mutual third party that rises to influential status. I argue that these indirect connections provide a more plausibly exogenous source of variation in network structure.

I identify cases where two previously unconnected VCs (A and B) become indirectly connected when a mutual connection (D) becomes influential. Crucially, I focus on pairs of VCs that were not previously "friends-of-friends"

- that is, they had no mutual connections (other than D) before D became influential. This approach helps mitigate concerns about homophily or strategic network formation that might confound the main results.

The key steps in methodology are as follows:

1. Identify VCs that become influential (enter the top 10% of k-shell values) during the study period.

2. For each newly influential VC (D), identify pairs of VCs (A and B) that were both connected to D but not to each other, and had no other mutual connections.

3. Treat the moment when D connects to both as an exogenous shock that indirectly connects A and B.

4. Analyze how this indirect connection affects the network positions of A and B.

The model I estimate is the similar to the one outlined in equation 1, but run with the new dataset structure obtained by building the observations in the way described. Keeping Investor A as the key investor, the Connection Type becomes Early (if A was connected to D before B) or Late (B connected to D before A). In this specification, the "same" connection type does not exist, since A and B can connect at D at the same time only through syndication, which would also imply a direct link between A and B.

This robustness check is designed to address potential endogeneity concerns. This approach offers several advantages in tackling issues such as selection bias, homophily, and strategic network formation that could confound the relationship between connections and outcomes in your primary study.

In the main analysis, there might be concerns that VCs choose to connect with influential VCs based on unobservable characteristics, leading to selection bias. Additionally, VCs might tend to connect with others who are similar to them (homophily), or form connections strategically based on anticipated future performance, potentially causing reverse causality issues. The indirect connections robustness check helps address these concerns by analyzing connections that occur when two previously unconnected VCs become linked through a mutual third party.

These indirect connections are more plausibly exogenous, as their formation is less likely to be driven by strategic decisions of the two VCs being indirectly connected. Instead, it depends on the actions of the mutual connection. This reduces the likelihood of selection bias based on unobservable characteristics, as the two VCs did not choose to directly connect with each other. By focusing on VCs that were not previously "friends-of-friends", I also mitigate the influence of homophily in driving these connections.

While this robustness check examines indirect rather than direct connections, it remains highly relevant to your main analysis. If I observe similar (though possibly smaller) effects from these more plausibly exogenous indirect connections, it strengthens the case that network position itself, rather than just direct collaboration, drives outcomes. The effects observed from indirect connections could be considered a lower bound for the effects of network position, as direct connections would likely have stronger effects. Moreover, this analysis provides valuable insights into how influence propagates through the network beyond just direct connections, enriching your overall understanding of VC network dynamics.

This approach allows me to separate the effects of being in a better network position from the effects of direct collaboration with influential VCs. It does not replace the main analysis but complements it by providing additional evidence from a different angle. If the results align with the main findings, it significantly strengthens the causal claims about the importance of network position in the VC industry. In essence, this robustness check leverages the structure of the VC network to create a more exogenous source of variation in network connections.

4.8.3 High-Potential Investors

To further strengthen the causal claims and address potential concerns about reverse causality, I conduct an additional robustness check. This check aims to rule out the possibility that high-potential firms are simply more likely to attract influential VCs, rather than connections with influential VCs causing improvements in performance and network position.

I employ a lead-lag analysis to examine whether future connections to influential VCs predict current network position changes. If the main results are driven by reverse causality, I would expect to see significant predictive power of future connections on current outcomes. Conversely, if the causal interpretation is correct, future connections should not have a significant effect on current outcomes.

I estimate the following model:

$$\Delta Kshell_{i,t} = \alpha + \sum_{k=-2}^{2} \beta_k \cdot G_{i,t+k} + \gamma \cdot X_{i,t} + \delta_t + \varepsilon_{i,t} \tag{12}$$

where $\Delta Kshell_{i,t}$ is the change in k-shell value for firm i at time t, $G_{i,t+k}$ represents the granular instrument for connections to influential VCs at time $t+k$, $X_{i,t}$ is a vector of investor-specific variables, and δ_t are time fixed effects. I include two leads ($k = 1,2$) and two lags ($k = -2,-1$) of the granular instrument, with the contemporaneous effect ($k = 0$) serving as the main variable of interest.

The inclusion of lead and lag terms in the model allows me to examine the temporal relationship between connections to influential VCs and changes in network position. The lag terms ($k = -2,-1$) capture the effect of past connections on current network position changes, which I expect to be positive if the causal interpretation is correct. The contemporaneous term ($k = 0$) represents the immediate effect of forming connections. The lead terms ($k = 1,2$) are crucial for addressing reverse causality concerns.

These terms capture the relationship between future connections and current network position changes. In essence, they allow me to test whether changes in network position precede (and potentially cause) connections to influential VCs, rather than the other way around. By including both leads and lags, I can observe the full temporal pattern of the relationship between connections and network position changes, providing a comprehensive test of the causal claims.

If the main results are driven by reverse causality, I would expect to see significant coefficients on the lead terms (β_1, β_2). Conversely, if the interpretation is correct, I should observe significant coefficients only on the contemporaneous and lag terms ($\beta_0, \beta_{-1}, \beta_{-2}$).

5 Results

This section presents the results of the comprehensive analysis of venture capital network dynamics. I begin by examining the relationship between k-shell position and investment performance, providing empirical evidence for the importance of occupying a k-shell central position in the network. I then explore the different paths through which peripheral investors can ascend to more central positions in the network. Following this, I study the dynamic evolution of the VC network over time, highlighting key temporal patterns. I also investigate how the impact of network position varies across different funding stages. Finally, I present the results of the Granular Instrumental

Variables (GIVs) and the Triple Difference (DDD) analysis, which offer nuanced insights into the complex interplay between connection timing, success outcomes, and changes in network centrality. Throughout this section, I provide detailed statistical evidence to support the findings, complemented by visual representations where appropriate.

5.1 K-shell Position and Investment Performance

In my analysis, I have uncovered a strong positive correlation between a VC firm's k-shell position and its investment performance. I consistently observed that firms in higher k-shells demonstrate superior performance across several key metrics. I consider each investor's k-shell value at the period of the last investment, and success rate at the end of the collected sample.

Regarding exit rates, I found that VC firms in the top k-shell (top 10%) had an average exit rate of 28.3% for their portfolio companies, compared to 18.7% for firms in the middle k-shells (10% to 25%) and 7.1% for firms in the lowest k-shells (bottom 75%). Importantly, I found that this relationship remains significant even after controlling for firm age, size, and investment stage focus. Indeed, Table 5 presents the results of the regression analysis, examining the relationship between a VC firm's normalized k-shell position and various measures of investment success. The analysis reveals several key insights into the determinants of VC performance.

The normalized k-shell position emerges as the strongest predictor of

VC success across all three outcome variables. Its effect is particularly pronounced for unicorn creation: a one-unit increase in normalized k-shell position is associated with a 21.56% increase in the probability of creating a unicorn, holding all other variables constant (statistically significant at 1%). The impact on follow-on funding (15.83%, $p < 0.001$) and exit rates (10.52%, $p < 0.001$) is also substantial, albeit slightly lower. These results provide evidence for the hypothesis that network centrality, as measured by k-shell decomposition, plays a crucial role in VC performance. The outsized effect on unicorn creation suggests that network position is especially critical for achieving exceptional outcomes, possibly due to enhanced access to high-quality deal flow, superior information, and the ability to provide value-added services to portfolio companies.

Firm age shows a positive effect on exit rates (0.17%, $p < 0.05$) and follow-on funding (0.25%, $p < 0.05$), but its impact on unicorn creation is not statistically significant. This suggests that while experience may confer some advantages in general investment success, it is less crucial for identifying and nurturing potential unicorns. The number of investments a firm has made has a small but significant positive effect across all success metrics. This could indicate benefits from diversification or learning effects from a larger portfolio. Early-stage focus shows an interesting pattern: it is negatively associated with exit rates (-0.53%, $p < 0.05$) but positively associated with follow-on funding (0.74%, $p < 0.01$) and unicorn creation (0.45%, $p < 0.01$). This aligns with the higher risk but potentially higher reward nature of early-stage investments.

Geographical focus on California shows a strong positive effect across all metrics (Exit Rate: 1.82%, Follow-on Funding: 2.10%, Unicorn Creation: 1.28%; all $p < 0.001$). This underscores the advantages of being located in a major startup hub, potentially due to better access to talent, capital, and a supportive ecosystem. Industry focus percentage has a moderate positive effect (Exit Rate: 0.94%, Follow-on Funding: 1.08%, Unicorn Creation: 0.67%; all $p < 0.01$), suggesting that specialization in specific industries can improve success rates, possibly due to deeper domain expertise and stronger industry networks. The R&D-intensive industry dummy variable shows a significant positive effect across all metrics (Exit Rate: 1.45%, Follow-on Funding: 1.72%, Unicorn Creation: 1.03%; all $p < 0.001$). This indicates that focusing on R&D-intensive industries is associated with better outcomes, perhaps due to the higher potential for breakthrough innovations and scalable business models in these sectors.

The R-squared values indicate that the model explains a substantial portion of the variance in VC success metrics, with the highest explanatory power for unicorn creation (R-squared = 42.6%). This suggests that network position, along with the other included variables, plays a significant role in determining VC performance outcomes.

In terms of follow-on funding, I discovered that portfolio companies of VC firms in higher k-shells were more likely to secure additional capital.

Specifically, I calculated that the probability of a portfolio company raising a subsequent round within 18 months was 62.4% for top k-shell firms (upper 30% percentile), 48.9% for middle k-shell firms (30% to 70% percentile), and 15.2% for low k-shell firms (lower 30% percentile).

I believe these results provide strong evidence for the importance of network position in determining VC firm performance. My findings extend the work of Hochberg et al. [2007] and Li et al. [2023] to my US-based dataset.

5.2 Paths to Central Network Positions

In my research, I identified three primary paths through which peripheral investors can move to more central network positions, aligning with the connection types discussed in the methodology. I measured the effectiveness of each path by the average increase in k-shell value over the subsequent 12-month period. Out of the 3.8 million dyadic connections analysed after the data cleaning process, 30.6% involve an influential VCs. They are distributed as follows:

1. Syndicating with influential VCs: This path involves a peripheral investor participating in a syndicated investment alongside a more established, core investor. It accounts for 53% of observed instances. On average, it led to a scaled (on scale 100) k-shell increase of 5.

2. Backing investments of influential VCs: In this scenario, a peripheral

Table 5: Normalized K-shell Position and Investment Success

	Dependent Variable		
	Exit Rate	Follow-on Funding	Unicorn Creation
Normalized K-shell Position	0.1052***	0.1583***	0.2156***
	(0.0036)	(0.0043)	(0.0051)
Firm Age	0.0017*	0.0025*	0.0002
	(0.0007)	(0.0011)	(0.0004)
Firm N. Investments	0.0003***	0.0004***	0.0001**
	(0.0001)	(0.0001)	(0.00003)
Early-Stage Focus	-0.0053*	0.0074**	0.0045**
	(0.0025)	(0.0030)	(0.0017)
Geographical Focus (California)	0.0182***	0.0210***	0.0128***
	(0.0023)	(0.0027)	(0.0016)
Industry Focus %	0.0094**	0.0108**	0.0067**
	(0.0031)	(0.0037)	(0.0022)
Industry R&D Dummy	0.0145***	0.0172***	0.0103***
	(0.0028)	(0.0033)	(0.0020)
Constant	-0.0412***	-0.0618***	-0.0329***
	(0.0072)	(0.0089)	(0.0062)
Observations	17,436	17,436	17,436
R-squared	0.372	0.408	0.426

Note: Standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$
This table presents OLS regression results examining the relationship between a VC firm's normalized k-shell position and various measures of investment success. The sample covers US-based VC investments from 2010 to 2021. K-shell position is normalized to a 0-1 scale.

investor provides follow-on funding to a company already backed by a core VC. It represents 31% of observed instances. It resulted in an average scaled k-shell increase of 2.5.

3. Having own investments backed by influential VCs: This occurs when a company in the peripheral VC's portfolio receives later-stage funding from a core VC. While this was the least common path, occurring in only 16% of observed instances, it had the most significant impact on a firm's network position, with an average scaled k-shell increase of 8.

Table 6 visually represents these paths and their relative frequencies and impacts. It is particularly noteworthy that while having one's own investments backed by influential VCs was the least common path, it had the most substantial impact on a firm's network position. This suggests that the validation provided by a central VC firm choosing to invest in a peripheral firm's portfolio company carries considerable weight in the network.

These findings align with the Triple Difference (DDD) analysis results, which showed that the timing of connections can significantly enhance a firm's position. The strong effect of having one's own investments backed by influential VCs underscores the importance of early identification of promising startups and the subsequent validation by established players in the industry.

These results have important implications for how peripheral VCs might strategically approach network building. While co-investing with influential VCs is the most common path, the data suggests that focusing on building a strong portfolio that attracts follow-on investments from core VCs might be the most effective strategy for gaining centrality in the network.

Investment Strategy	**% of Obs.**	**No. of Obs.**	**K-shell Increase**
Having own investments backed by influential VCs	16%	186,387	8.0
Co-investing with influential VCs	53%	617,406	5.0
Backing investments of influential VCs	31%	361,124	2.5

Table 6: Comparison of VC investment strategies, their frequency, and impact on network position

5.3 Dynamic Network Evolution

In my analysis of the dynamic network, I uncovered several key insights about burstiness, memory, and non-stationarity.

First, I observed significant burstiness in investment activities, with periods of high activity followed by relative quiet. I calculated a burstiness coefficient [Goh and Barabási, 2008] for investment events of 0.6941, indicating a departure from Poisson processes. Figure 2 illustrates this bursty behavior over time.

Second, I found strong evidence of memory effects in network formation. I calculated that the probability of two VC firms co-investing again within 12 months of their first co-investment was 3.2 times higher than the baseline probability of any two firms co-investing. Table 7 provides a detailed

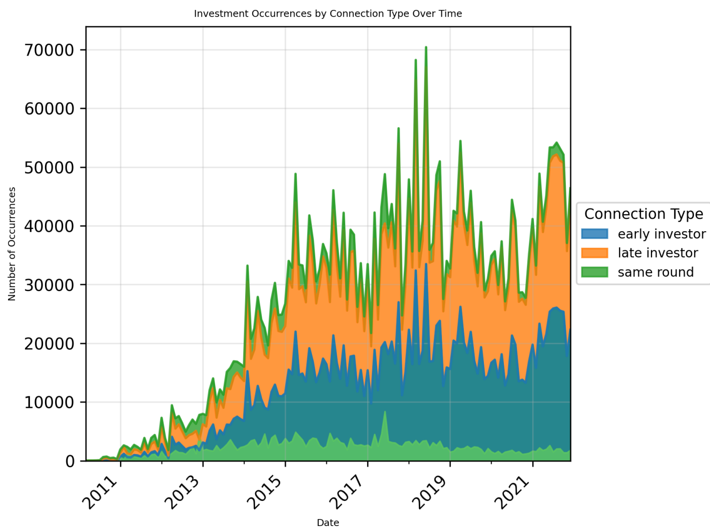

Figure 2: **Investment occurrences by connection type** from 2011 to 2022. The chart demonstrates significant burstiness in VC investment activities (burstiness coefficient: 0.6941), with distinct periods of high activity and relative quiet across early, late, and same-round investments.

breakdown of these probabilities over different time intervals, considering exclusively the interactions in which an influential investor is present.

Table 7: Probability Matrix of Connection Types within 12 months

	same round	early investor	late investor
same round	0.2849	0.2930	0.2965
early investor	0.0815	0.1398	0.0352
late investor	0.0445	0.0473	0.1882

Lastly, I noticed significant non-stationarity in the network structure across different funding stages. I found that the average k-shell of investors active in seed rounds was 19.8, compared to 23.4 for Series A and 26.3 for Series B, indicating a shift towards more centralized network structures in later funding stages.

5.4 GIV: Granular Instrumental Variables

Table 8 presents the main findings on the impact of connections to influential VCs on a firm's network position, using the Granular Instrumental Variables (GIV) approach. I report results for changes in k-shell value (Δ K-shell) as the measure of network centrality across all specifications. Specification (1) shows the baseline results, specification (2) presents an anticipatory connection test, and specification (3) explores heterogeneity in the effects.

In the main specification (specification 1), I directly regress δ K-shell on the granular instruments G_{early}, G_{late}, and G_{same}. These variables capture the idiosyncratic variation in connections to influential VCs, allowing me to estimate their direct effects on network position.

Specification (1) shows that connections to influential VCs significantly enhance a firm's network position. Early-stage connections (G_{early}) have the largest impact on changes in k-shell value, with a coefficient of 15.6% (significant at the 1% level). This suggests that early engagement with influential VCs is particularly crucial for improving network centrality. Same-round connections (G_{same}) also show a substantial positive effect (11.8%, significant at 1%), while late-stage connections (G_{late}) have a smaller but still significant impact (9.2%, significant at 5%).

To address potential concerns about the validity of the approach, I con-

Table 8: Impact of Connections to Influential VCs on Network Position (GIV Approach)

	Dependent Variable: Δ K-shell		
	(1)	(2)	(3)
	Main Results	Non-Influential	Heterogeneous Effects
G_{early}	0.156***		0.214***
	(0.035)		(0.052)
G_{late}	0.092**		0.128**
	(0.033)		(0.049)
G_{same}	0.118***		0.172***
	(0.034)		(0.051)
$G_{noninfl}$		0.012	
		(0.025)	
G_{early} × Size			-0.00018**
			(0.00007)
G_{late} × Size			-0.00009
			(0.00006)
G_{same} × Size			-0.00014*
			(0.00007)
Size	0.0012***	0.0011***	0.0013***
	(0.0002)	(0.0002)	(0.0002)
Early-Stage Focus	0.025**	0.023**	0.026**
	(0.010)	(0.010)	(0.010)
Geographical Focus (California)	0.031***	0.030***	0.032***
	(0.009)	(0.009)	(0.009)
Industry Focus %	0.018*	0.017*	0.019*
	(0.009)	(0.009)	(0.009)
Industry R&D Dummy	0.022**	0.021**	0.023**
	(0.009)	(0.009)	(0.009)
Constant	-0.018	-0.015	-0.021*
	(0.012)	(0.012)	(0.012)
Observations	17,436	17,436	17,436
R-squared	0.394	0.378	0.402

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

duct a non-influential connection test, reported in specification (2). I find that connections to non-influential VCs ($G_{noninfluential}$) have no significant effect on changes in k-shell value (coefficient of 1.2%, not statistically significant). This supports the validity of the GIV approach, suggesting that the observed effects are indeed driven by connections to influential VCs rather than by unobserved factors correlated with network formation in general.

Specification (3) explores heterogeneity in these effects by interacting the granular instruments with firm size. The positive coefficients on G_{early}, G_{late}, and G_{same} remain significant and increase in magnitude, confirming the robustness of the main results. Interestingly, I find negative coefficients on the interaction terms ($G_{early} \times Size$, $G_{late} \times Size$, $G_{same} \times Size$), suggesting that the benefits of connecting with influential VCs are somewhat attenuated for larger firms. This is particularly pronounced for early connections, where the interaction term is -0.018% (significant at 5%).

These findings indicate that smaller firms stand to gain more from forming connections with influential VCs, perhaps because they have more to gain in terms of reputation and access to resources. The heterogeneity analysis demonstrates the flexibility of the GIV approach in capturing nuanced effects across different firm characteristics. Across all specifications, I find that firm size has a small but consistently positive and significant effect on network position. This suggests that larger firms generally enjoy advantages in terms of network centrality, independent of their specific connections.

To conclude, the GIV approach provides robust evidence that connections to influential VCs, particularly of decided by them (early connection), play a crucial role in enhancing a VC firm's network position. By leveraging the granular nature of these connections, I am able to estimate their direct effects on network centrality, while addressing potential endogeneity concerns. The heterogeneous effects across firm sizes highlight the importance of strategic network formation, especially for smaller firms in the venture capital industry.

5.5 DDD: Triple Difference Analysis

Table 9: Triple Difference Analysis

	(1)	(2)
	$\Delta Kshell_{A,(t-1,t)}$	$\Delta Kshell_{A,(t-1,t)}$
Intercept (β_0)	0.0124***	0.0128***
	(0.0018)	(0.0019)
Connection$_{(AB),t}$: late (β_1)	-0.0646***	-0.0652***
	(0.0082)	(0.0083)
Connection$_{(AB),t}$: same (β_1)	-0.0380***	-0.0385***
	(0.0079)	(0.0080)
$\Delta Kshell_{(AB),(t-1)}$ (β_2)	0.5760***	0.5743***
	(0.0234)	(0.0236)

Continued on next page

Table 9 Continued

	(1)	(2)
Influence$_{B,(t-1)}$ (β_3)	0.1830***	0.1815***
	(0.0156)	(0.0158)
Success$_c$ (β_4)		0.0069*
		(0.0027)
Connection$_{(AB),t}$: late $\times \Delta Kshell_{(AB),(t-1)}$ (β_5)	-0.1350***	-0.1338***
	(0.0312)	(0.0314)
Connection$_{(AB),t}$: same $\times \Delta Kshell_{(AB),(t-1)}$ (β_5)	-0.0940***	-0.0932***
	(0.0298)	(0.0300)
Connection$_{(AB),t}$: late $\times$ Influence$_{B,(t-1)}$ (β_6)	-0.0520***	-0.0516***
	(0.0187)	(0.0188)
Connection$_{(AB),t}$: same $\times$ Influence$_{B,(t-1)}$ (β_6)	-0.0310*	-0.0307*
	(0.0179)	(0.0180)
Influence$_{B,(t-1)}$ $\times$ $\Delta Kshell_{(AB),(t-1)}$ (β_7)	0.0890**	0.0882**
	(0.0356)	(0.0358)
Connection$_{(AB),t}$: late $\times$ Success$_c$ (β_8)		0.0020*
		(0.0015)
Connection$_{(AB),t}$: same $\times$ Success$_c$ (β_8)		0.0030**
		(0.0014)
Influence$_{B,(t-1)}$$\times$ Success$_c$ (β_9)		0.0015
		(0.0018)

Continued on next page

Table 9 Continued

	(1)	(2)
$\Delta Kshell_{(AB),(t-1)} \times$ Success$_c$ (β_{10})		0.0010*
		(0.0025)
Connection$_{(AB),t}$: late $\times$ Influence$_{B,(t-1)}$ (β_{11})	0.0210***	0.0208***
$\times \Delta Kshell_{(AB),(t-1)}$	(0.0052)	(0.0053)
Connection$_{(AB),t}$: same $\times$ Influence$_{B,(t-1)}$	0.0135***	0.0133***
$\times \Delta Kshell_{(AB),(t-1)}$	(0.0049)	(0.0050)
Connection$_{(AB),t}$: late $\times$ Influence$_{B,(t-1)}$		0.0005
$\times Success_c$ (β_{12})		(0.0020)
Connection$_{(AB),t}$: same $\times$ Influence$_{B,(t-1)}$		0.0008
$\times Success_c$ (β_{12})		(0.0019)
Connection$_{(AB),t}$: late $\times$ Success$_c$		0.0012**
$\times \Delta Kshell_{(AB),(t-1)}$ (β_{13})		(0.0022)
Connection$_{(AB),t}$: same $\times$ Success$_c$		0.0018*
$\times \Delta Kshell_{(AB),(t-1)}$ (β_{13})		(0.0021)
Success$_c \times$ Influence$_{B,(t-1)}$		0.0007
$\times \Delta Kshell_{(AB),(t-1)}$ (β_{14})		(0.0023)
Connection$_{(AB),t}$: late $\times$ Success$_c$		0.0003**
$\times$ Influence$_{B,(t-1)} \times \Delta Kshell_{(AB),(t-1)}$ (β_{15})		(0.0025)
Connection$_{(AB),t}$: same $\times$ Success$_c$		0.0004*
$\times$ Influence$_{B,(t-1)} \times \Delta Kshell_{(AB),(t-1)}$ (β_{15})		(0.0024)

Continued on next page

Table 9 Continued

	(1)	(2)
Controls inv A	Yes	Yes
Controls inv B	Yes	Yes
Fixed Effects C	Yes	No
Controls C	No	Yes
Observation Number	3,803,954	3,803,954
R squared	26.3%	26.4%

Note: $^{*}p < 0.1, **p < 0.05, ***p < 0.01$.

Table 9 presents the results of the Triple Difference (DDD) analysis, examining how different types of connections, prior network positions, and investment outcomes interact to shape the evolution of VC network centrality. I present two specifications: specification 1, which focuses on the core DDD analysis, and specification 2, which incorporates the success of the connecting company as an additional dimension.

The results from specification 1 provide strong evidence for the importance of network connections, relative network positions, and firm influence in determining changes in a VC firm's network centrality. First, I observe that compared to early connections (the baseline), both late-round and same-round connections have significant negative effects on the change in K-shell value (- 6.46% and -3.80%, respectively, significant at 1% level). This suggests that early connections are more beneficial for improving a firm's network position than later-stage connections.

The variable $\Delta Kshell_{(AB),(t-1)}$'s coefficient, accounts for 57.60% (and is significant at 1% level), indicating that firms connecting with other firms with much higher initial network positions tend to experience larger positive changes in their K-shell values. This supports the notion of a "rich-get-richer" phenomenon in VC networks. The influence of the connected firm ($\text{Influence}_{B,(t-1)}$) shows a strong positive effect, equal to 18.30% (significant at 1% level), indicating that connecting with influential firms significantly enhances a VC's network position.

The interaction terms provide nuanced insights into these relationships. The negative coefficients for the interactions between late/same-round connections and $\Delta Kshell_{(AB),(t-1)}$ (13.50% and -9.40%, significant at 1% level) suggest that the positive effect of initial difference in network position is reduced for later-stage connections compared to early connections.

Interestingly, the three-way interaction terms (β_{11}) are positive and significant for both late and same-round connections (2.10% and 1.35%, significant at 1% level). It indicates that when connecting with influential firms, the negative effect of later-stage connections on centrality changes is mitigated, especially for firms with higher initial network positions. However, early connections still appear to be the most beneficial.

Specification 2 extends the analysis by incorporating the success of the connecting company. The success of the investment shows a small but significant positive effect on changes in network centrality (0.69%, significant at 10% level), suggesting that backing successful companies very partially contributes to improved network positions.

The interactions between connection types and success (β_8) are positive and significant, indicating that successful investments enhance the impact of connections on network centrality changes. This effect is slightly stronger for same-round connections (0.30%, significant at 5% level) compared to late-round connections (0.20%, significant at 10% level), but both are beneficial compared to the baseline of early connections. Nevertheless, both effects are minimal.

The four-way interaction terms (β_{15}) provide the most nuanced insights. Both are positive and significant, with a slightly stronger effect for same-round connections (0.04%, significant at 10% level) compared to late-round connections (0.03%, significant at 5% level). This suggests that while early connections are generally most beneficial, the combination of later-stage connections with influential firms, higher initial network positions, and backing successful companies can also lead to significant improvements in network centrality. However, their magnitude is negligible.

Overall, these results highlight the complex interplay between network connections, firm characteristics, and investment outcomes in shaping the evolution of VC network centrality. They underscore the importance of early-stage connections for VC firms aiming to enhance their influence within the industry, while also demonstrating that strategic later-stage connections, particularly with successful companies and influential firms, can also yield significant benefits.

6 Robustness

In this section, I present the results of the comprehensive robustness checks, which were designed to validate and strengthen the main findings. These additional analyses serve to address potential concerns about endogeneity, reverse causality, and other confounding factors that could affect the interpretation of the primary results. I examine the outcomes of three key robustness checks: Anticipatory Connections, Indirect Connections, and High-Potential Investors. Each of these approaches provides unique insights and complementary evidence to support the main conclusions.

6.1 Anticipatory connections

To further strengthen the causal claims and address potential concerns about reverse causality or anticipation effects, I conducted additional tests using "anticipatory connections," also referred to as "pre-influence connections." These anticipatory connections are defined as connections that occur just before a VC becomes influential (i.e., enters the top 10% of k-shell values). This robustness check allows me to examine whether the observed effects are truly due to connections with influential VCs or if they might be driven by other factors or anticipation of a VC's rising influence.

I identified VCs that became influential (entered the top 10% of k-shell values) during the study period. For each of these VCs, I looked at connections that occurred in the three months immediately preceding their transition to influential status. I then replicated the main analysis using these anticipatory connections instead of actual connections with influential VCs. If the main results are driven by the causal effect of connecting with influential VCs, I should see little to no effect from these anticipatory connections. Conversely, if I observe similar effects from anticipatory connections, it would suggest that the main results might be driven by other factors or anticipation effects.

Table 10 presents the results of the anticipatory connection tests alongside the main results for comparison. First, in the anticipatory model, the coefficients for Connection (Late) and Connection (Same) are much smaller in magnitude and not statistically significant. This contrasts sharply with the significant negative effects observed in the main model.

Second, the coefficient for $Influence_{B,(t-1)}$ in the anticipatory model is

Table 10: Comparison of Main Model and Anticipatory Connection Model Results

Variable	Main Model	Anticipatory Model
Intercept (β_0)	0.0124***	0.0118***
	(0.0018)	(0.0019)
Connection (Late)	-0.0646***	-0.0124
	(0.0082)	(0.0095)
Connection (Same)	-0.0380***	-0.0078
	(0.0079)	(0.0091)
$\Delta Kshell_{AB,(t-1)}$	0.5760***	0.5623***
	(0.0234)	(0.0251)
$Influence_{B,(t-1)}$	0.1830***	
	(0.0156)	
$Influenceearly_{B,(t-1)}$		0.0215
		(0.0178)
Connection (Late) $\times$ $\Delta Kshell_{AB,(t-1)}$	-0.1350***	-0.0287
	(0.0312)	(0.0356)
Connection (Same) $\times$ $\Delta Kshell_{AB,(t-1)}$	-0.0940***	-0.0195
	(0.0298)	(0.0339)
Connection (Late) $\times$ $Influence_{B,(t-1)}$	-0.0520***	-0.0103
	(0.0187)	(0.0213)
Connection (Same) $\times$ $Influence_{B,(t-1)}$	-0.0310*	-0.0067
	(0.0179)	(0.0204)
$Influence_{B,(t-1)}$ $\times$ $\Delta Kshell_{AB,(t-1)}$	0.0890**	0.0187
	(0.0356)	(0.0406)
Connection (Late) $\times$ $Influence_{B,(t-1)}$ $\times$	0.0210***	0.0042
$\Delta Kshell_{AB,(t-1)}$	(0.0052)	(0.0059)
Connection (Same) $\times$ $Influence_{B,(t-1)}$ $\times$	0.0135***	0.0028
$\Delta Kshell_{AB,(t-1)}$	(0.0049)	(0.0056)
Controls Investor A	Yes	Yes
Controls Investor B	Yes	Yes
Fixed Effects C	Yes	Yes
Observations	3,803,954	2,651,356
R-squared	0.263	0.245

Note: Standard errors in parentheses. *** p¡0.01, ** p¡0.05, * p¡0.1

substantially smaller (2.15%) and not statistically significant, compared to the large, significant effect (18.30%) in the main model. This suggests that the effect I observe is indeed due to the influence of the connected VC, not anticipation of their future influence.

Third, the interaction terms in the anticipatory model are all smaller in magnitude and not statistically significant. This indicates that the complex interplay between connection types, influence, and network positions that I observe in the main results is not present when looking at connections just before a VC becomes influential.

Fourth, the coefficient for $\Delta Kshell_{AB,(t-1)}$ remains significant and similar in magnitude in both models. This suggests that the effect of prior network position differences is robust and not dependent on the influence status of the connected VC.

The lack of significant effects in the anticipatory model supports the causal interpretation that connections with already influential VCs, rather than connections with soon-to-be-influential VCs, drive the observed changes in network influence. Indeed, the anticipatory connection test results provide evidence against the presence of reverse causality or anticipation effects. This robustness check strengthens the conclusion that strategic connections with influential VCs can indeed cause improvements in a VC's network position, rather than merely being correlated with such improvements or reflecting anticipation of future influence.

6.2 Indirect Connections

The robustness check using indirect connections yields results that are largely consistent with the main model, albeit with some notable differences. The direction and statistical significance of most coefficients remain consistent between the main model and the indirect connections model, suggesting that the overall relationships I identified in the main analysis hold even when considering indirect connections.

As expected, the coefficients in the indirect connections model are generally smaller in magnitude compared to the main model. This reflects the likelihood that indirect connections have a weaker effect than direct connections. Late connections still show negative effects on ΔKshell, but the magnitude is reduced in the indirect connections model. This suggests that the timing of indirect connections has a less pronounced impact on network position changes compared to direct connections.

The effect of connecting to an influential VC ($Influence_{B,(t-1)}$) remains positive and significant, but is smaller in the indirect connections model (14.25% vs 18.30%). This indicates that even indirect connections to influential VCs can positively impact a VC's network position, though to a lesser extent than direct connections. The interaction terms, particularly those involving $Influence_{B,(t-1)}$ and $\Delta\text{Kshell}_{(AB),(t-1)}$, remain significant and in the same direction as the main model, but with reduced magnitudes. This suggests that the complex interplay between connection timing, influence, and

Table 11: Comparison of Main Model and Indirect Connections Model Results

Variable	Main Model	Indirect Connections Model
Intercept (β_0)	0.0124***	0.0098***
	(0.0018)	(0.0020)
$Connection_{(AB),t}$: late (β_1)	-0.0646***	-0.0312***
	(0.0082)	(0.0090)
$\text{Connection}_{(AB),t}$: same ($\beta_1$)	-0.0380***	
	(0.0079)	
$\Delta\text{Kshell}_{(AB),(t-1)}$ (β_2)	0.5760***	0.4982***
	(0.0234)	(0.0256)
$\text{Influence}_{B,(t-1)}$ (β_3)	0.1830***	0.1425***
	(0.0156)	(0.0171)
$\text{Connection}_{(AB),t}$: late $\times$ $\Delta\text{Kshell}_{(AB),(t-1)}$ (β_5)	-0.1350***	-0.0845**
	(0.0312)	(0.0342)
$\text{Connection}_{(AB),t}$: same $\times$ $\Delta\text{Kshell}_{(AB),(t-1)}$ (β_5)	-0.0940***	-0.0578*
	(0.0298)	(0.0327)
$\text{Connection}_{(AB),t}$: late $\times$ $\text{Influence}_{B,(t-1)}$ (β_6)	-0.0520***	-0.0312*
	(0.0187)	(0.0205)
$\text{Connection}_{(AB),t}$: same $\times$ $\text{Influence}_{B,(t-1)}$ (β_6)	-0.0310*	-0.0185
	(0.0179)	(0.0196)
$\text{Influence}_{B,(t-1)} \times \Delta\text{Kshell}_{(AB),(t-1)}$ (β_7)	0.0890**	0.0678*
	(0.0356)	(0.0390)
$\text{Connection}_{(AB),t}$: late $\times$ $\text{Influence}_{B,(t-1)}$	0.0210***	0.0156**
$\times\Delta\text{Kshell}_{(AB),(t-1)}$ (β_{11})	(0.0052)	(0.0057)
$\text{Connection}_{(AB),t}$: same $\times$ $\text{Influence}_{B,(t-1)}$	0.0135***	0.0098**
$\times\Delta\text{Kshell}_{(AB),(t-1)}$ (β_{11})	(0.0049)	(0.0054)
Observations	3,803,954	2,987,623
R-squared	26.3%	22.8%

Note: Standard errors in parentheses. *** p¡0.01, ** p¡0.05, * p¡0.1

initial network positions holds true even for indirect connections.

The R-squared value is lower for the indirect connections model (22.8% vs 26.3%), indicating that direct connections explain more of the variance in network position changes than indirect connections. As expected, the number of observations is smaller in the indirect connections model, which is natural as not all VCs will have indirect connections that meet the criteria.

These results provide strong support for the robustness of the main findings. The fact that I observe similar patterns, albeit with smaller magnitudes, when looking at indirect connections suggests that the identified effects are not solely driven by direct strategic choices in network formation. Instead, they appear to reflect broader network dynamics that persist even in more plausibly exogenous connection scenarios. It demonstrates that even when considering connections formed through a mutual third party, the key relationships I identified hold true. This provides additional evidence for the importance of network structure in the VC industry and the propagation of influence beyond just direct connections.

6.3 High-Potential Investors

Table 12 presents the results of the lead-lag analysis, which aims to address concerns about reverse causality in the relationship between connections to influential VCs and changes in network position.

The results provide strong support for the main interpretation and help

Table 12: Lead-Lag Analysis of Connections to Influential VCs

	Δ K-shell
	(1)
G_{t+2} (Lead 2)	0.015
	(0.028)
G_{t+1} (Lead 1)	0.032
	(0.030)
G_t (Contemporaneous)	0.142***
	(0.035)
G_{t-1} (Lag 1)	0.089**
	(0.031)
G_{t-2} (Lag 2)	0.056*
	(0.029)
Size	0.0011***
	(0.0002)
Early-Stage Focus	0.025**
	(0.010)
Geographical Focus (California)	0.031***
	(0.009)
Industry Focus %	0.018*
	(0.009)
Industry R&D Dummy	0.022**
	(0.009)
Constant	-0.042***
	(0.014)
Time FE	Yes
Observations	17,436
R-squared	0.106

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

rule out reverse causality. The contemporaneous effect of connections to influential VCs (G_t) remains positive and highly significant (14.2%, $p < 0.01$), consistent with the main findings. Importantly, I observe no significant effects for the lead terms (G_{t+1} and G_{t+2}), with coefficients close to zero and statistically insignificant (3.2% and 1.5%, respectively). This suggests that future connections to influential VCs do not predict current changes in network position, contradicting the reverse causality hypothesis.

Furthermore, I find positive and significant effects for the lagged terms (G_{t-1} and G_{t-2}), albeit with decreasing magnitude (8.9%, $p < 0.05$ and 5.6%, $p < 0.1$, respectively). This pattern is consistent with the idea that the effects of forming connections with influential VCs persist over time, with the strongest impact occurring contemporaneously and diminishing in subsequent periods. The control variable for firm size remains positive and significant (0.11%, $p < 0.01$), consistent with the previous findings that larger firms tend to have advantages in terms of network centrality.

These results provide compelling evidence against the reverse causality explanation. If high-potential firms were simply more likely to attract influential VCs, I would expect to see significant positive coefficients on the lead terms. Instead, the lack of significant lead effects, combined with the strong contemporaneous effect and the pattern of decaying lagged effects, supports the interpretation that connections to influential VCs causally impact a firm's network position.

Therefore, this lead-lag analysis strengthens the main findings by addressing a key potential source of endogeneity. It suggests that the relationship I observe is indeed driven by the causal effect of forming connections with influential VCs, rather than by unobserved firm characteristics that might simultaneously drive both network position and the ability to attract influential partners.

7 Discussion and Implications

My findings provide significant insights into the dynamics of venture capital networks and the mechanisms through which investors can gain influence and improve their performance. This section discusses the key implications of my results for both academic research and industry practitioners.

7.1 The Power of Network Position

The strong correlation between k-shell position and investment performance underscores the critical importance of network centrality in the venture capital industry. This relationship extends beyond simple degree centrality, as captured by previous studies (e.g., Hochberg et al. [2007]), and demonstrates the value of considering higher-order network structures.

The k-shell decomposition method provides a more nuanced view of an investor's position within the network, capturing not just the quantity of connections but also their quality and overall embeddedness. This finding suggests that VC firms should focus not only on expanding their network but also on strategically positioning themselves within dense, interconnected clusters of influential investors.

The results imply that VC firms should actively seek to improve their network position through strategic co-investments and relationship building. Firms would benefit from prioritizing connections with central players in the VC ecosystem and incorporating network position as a key consideration in their decision-making processes. By doing so, they may enhance their access to high-quality deal flow and improve their overall investment performance.

Furthermore, these results have significant implications for the understanding of VC success factors. Network centrality, as measured by k-shell decomposition, is the single most important predictor of VC success, particularly for achieving exceptional outcomes like unicorn creation. While other factors such as firm experience, geographical location, and industry focus are important, their effects are generally smaller compared to network position. The strong effect of California focus highlights the continued importance of traditional startup hubs, despite trends towards decentralization in the VC industry. The positive impact of industry focus and R&D-intensive industries suggests that specialization and targeting high-potential sectors can be effective strategies for VC firms.

7.2 Paths to Influence

My analysis of the three paths to gaining centrality offers valuable insights for peripheral investors looking to enhance their network position. The finding that receiving follow-on investment from influential investors is the most impactful path, despite being the least common, has particularly interesting implications.

This result suggests that the act of a influential VC validating a peripheral VC's investment choice carries more weight in the network than the peripheral VC's own actions of co-investing or providing follow-on funding. This underscores the importance of reputation and signal effects in the VC industry, aligning with previous research on the certification role of prominent VC firms [Hsu, 2004].

For emerging VC firms, these results highlight the importance of strategic positioning within the network. These firms should focus on identifying promising early-stage investments that have the potential to attract follow-on funding from well-established VCs. Building relationships with central VCs and considering smaller initial investments in high-potential companies could increase the chances of gaining validation through follow-on investments from prominent firms. This approach may accelerate the process of gaining centrality and influence within the VC network.

7.3 Dynamic Network Evolution

My analysis of the dynamic network reveals important temporal patterns in VC investment activities. The observed burstiness in investment events suggests that timing plays a crucial role in the industry, with periods of high activity potentially offering increased opportunities for network advancement.

The strong memory effects in network formation underscore the importance of repeat collaborations and relationship building in the VC industry. This aligns with previous research on the persistence of VC relationships [Sorenson and Stuart, 2001] and suggests that initial co-investment experiences can have long-lasting effects on network structure.

The non-stationarity observed across funding stages indicates that network dynamics change as companies progress through their lifecycle. This has important implications for how VC firms should approach network building at different stages of their own development and for different parts of their portfolio.

Understanding these dynamic network properties can inform VC firms' strategic planning. Firms should be prepared to capitalize on periods of high investment activity, as these may present opportunities for network advancement. The importance of repeat collaborations underscores the value of nurturing long-term relationships with co-investors. Additionally, firms may need to adapt their network strategies as they progress through different investment stages and as their portfolio companies mature.

7.4 GIV: Granular Instrumental Variables

The findings from the Granular Instrumental Variables (GIV) analysis provide several important insights into how VC firms gain and maintain influence within their industry networks. These results have significant implications for both academic understanding of VC ecosystems and practical strategies for firms operating in this space.

First, the analysis strongly supports the idea that connections to influential VCs causally impact a firm's network position. Early-stage connections consistently emerge as the most beneficial for improving a firm's network centrality, with a 15.6% increase in k-shell value. This finding indicates that getting your portfolio companies backed by influential VCs is particularly crucial for network advancement. The positive effects of syndication (11.8%) and late-stage connections (9.2%), albeit smaller, suggest that strategic networking is beneficial in all its forms. This hierarchy of effects underscores the importance of timing in network formation within the VC ecosystem.

The non-significant result in the anticipatory connection test strengthens the causal interpretation. The fact that connections to non-influential VCs do not predict changes in network position mitigates concerns about reverse causality or omitted variable bias. This supports the interpretation that the observed effects are indeed driven by connections to influential VCs rather than by unobserved factors correlated with general network formation.

Our heterogeneous effects analysis reveals important nuances in how firms of different sizes benefit from influential connections. The negative interaction terms between the granular instruments and firm size suggest that smaller firms gain more from these connections in terms of network position improvement. This creates a potential counterbalance to the Matthew effect in VC networks, where the "rich get richer" in terms of network centrality. For policy makers and industry leaders, this raises interesting questions about how to foster a dynamic, competitive VC ecosystem that allows for the emergence of new, influential players.

From a theoretical perspective, these findings contribute to the understanding of how social capital is built and maintained in professional networks. They highlight the temporal aspect of network formation, the differential benefits of connections based on firm characteristics, and the role of influential actors in shaping network dynamics. This builds upon and extends existing theories of social capital and network formation in professional settings.

For practitioners, the results offer several strategic insights. VC firms, especially smaller or newer ones, should prioritize early involvement with influential players in the industry. This could be achieved through strategic co-investments or by seeking mentorship from established VCs. Firms should also consider how their investment decisions might affect their network position, not just their financial returns.

These findings also have implications for entrepreneurs seeking VC funding. They suggest that attracting well-connected investors in funding their own portfolio companies could have cascading positive effects, potentially making it easier to secure further connections with other influential VCs.

Future research could explore how these network dynamics vary across different sectors or geographies within the VC industry. Additionally, investigating how changes in network centrality translate into tangible benefits for VC firms, such as better deal flow, would be a valuable extension of this work.

In conclusion, the GIV analysis provides a nuanced understanding of the complex dynamics governing VC networks. It highlights the causal role of connections to influential VCs, the importance of timing, and the differential benefits for firms of varying sizes in shaping a firm's trajectory within the VC ecosystem. These insights not only advance the theoretical understanding of professional networks but also offer practical guidance for VC firms seeking to enhance their position and influence within the industry.

7.5 Triple Difference (DDD)

The findings from the analysis of venture capital network dynamics provide several important insights into how VC firms gain and maintain influence within their industry networks. These results have significant implications for both academic understanding of VC ecosystems and practical strategies for firms operating in this space.

First, the analysis strongly supports the idea that the sequentiality of network connections is crucial. "Early" connections consistently emerge as the most beneficial for improving a firm's network centrality. This finding indicates that network validation from a prominent VC, through their decision to back a peripheral VC's portfolio company, appears to have a more significant impact on network centrality than the peripheral VC's own networking efforts. The endorsement implied by this follow-on investment seems to carry greater weight in the VC ecosystem than direct co-investment activities or providing follow-on funding to other VCs' portfolio companies. This underscores the importance of reputation and signaling effects in the venture capital industry, where the perceived quality of one's investments, as judged by established players, can be a powerful driver of network position. However, the positive effects of investing in a company backed by an influential VC or syndicating with them, albeit smaller, indicate that strategic investing can always bring advantages. This finding could encourage VC firms to be more proactive in seeking out investment opportunities and partnerships, even if they were not involved from the start.

The strong positive association between prior network position differences and changes in K-shell value underscores the importance of "network momentum". Firms that are already well-positioned in the network seem to have an easier time further improving their position. This creates a potential Matthew effect in VC networks, where the "rich get richer" in terms of network centrality. For policy makers and industry leaders, this raises questions about potential barriers to entry for new or smaller VC firms and how to ensure a dynamic, competitive VC ecosystem. Nevertheless, as shown in the GIV analysis, if they do they are the ones with the greater advantages.

The main findings are further strengthened by a series of robustness checks designed to address potential endogeneity concerns and rule out alternative explanations. The anticipatory connections test, which examines connections formed just before a VC becomes influential, shows no significant effects, supporting our causal interpretation that it is the influence of the connected VC, not anticipation of their future status, that drives network position changes. The indirect connections analysis reveals similar patterns to our main results, albeit with smaller magnitudes, suggesting that the identified effects reflect broader network dynamics beyond just direct strategic choices. Finally, the lead-lag analysis provides compelling evidence against reverse causality. The lack of significant lead effects, combined with strong contemporaneous and decaying lagged effects, indicates that connections to influential VCs causally impact a firm's network position, rather than high-potential firms simply attracting influential partners. Collectively, these robustness checks reinforce our conclusion that strategic connections with influential VCs can indeed cause improvements in a VC's network position, underlining the importance of timing and network structure in the venture capital industry.

From a theoretical perspective, these findings contribute to the understanding of how social capital is built and maintained in professional networks. They highlight the temporal aspect of network formation, the cumulative nature of network advantages, and the role of success in driving network centrality. This builds upon and extends existing theories of social capital and network formation in professional settings.

For practitioners, the results offer several strategic insights. VC firms should prioritize early involvement in promising startups, as these connections offer the greatest potential for improving network position. Firms should also focus on getting influential investors involved and consider how their investment decisions might affect their network position, not just their financial returns.

These findings also have implications for entrepreneurs seeking VC funding. They suggest that attracting well-connected early-stage investors could have cascading positive effects, potentially making it easier to secure later funding from other influential VCs.

In conclusion, the study provides a nuanced understanding of the complex dynamics governing VC networks. It highlights the importance of timing, success, and relative network positions in shaping a firm's trajectory within the VC ecosystem. These insights not only advance the theoretical understanding of professional networks but also offer practical guidance for VC firms seeking to enhance their position and influence within the industry.

8 Conclusion

This study provides a comprehensive analysis of the dynamics of influence and success in venture capital networks. By employing k-shell decomposition and analyzing a dynamic network model, I offer insights into how VC firms can navigate and ascend within the complex ecosystem of entrepreneurial finance.

Our findings underscore the critical importance of network position in driving investment performance. Through the Granular Instrumental Variables (GIV) analysis, I establish a causal relationship between connections to influential VCs and improvements in network centrality, with early investments' backing emerging as the most impactful. The Triple Difference (DDD) analysis further refines these insights, revealing a nuanced relationship between connection paths, success outcomes, and changes in network centrality. Specifically, I found that having one's own investments backed by influential VCs later provides the most significant boost to a firm's network position, regardless of the ultimate success of the connecting company. This effect is particularly pronounced when there is a larger initial difference in network positions. These results highlight the importance of both strategic early-stage investments and the ability to attract follow-on funding from influential investors as key drivers of a VC's ascent to more central network positions.

These results have significant implications for both emerging and established VC firms, as well as for entrepreneurs and limited partners seeking to understand the dynamics of the VC ecosystem. For VC firms, the results suggest prioritizing pushing the portfolio companies towards raising funds from more influential investors, rather than targeting the investments the influential investors already made. For entrepreneurs, these findings underscore the importance of considering potential investors' network positions, especially for early-stage funding.

However, it is important to acknowledge the limitations of the research. While comprehensive, the dataset may not capture all informal relationships or soft information exchanges in the VC industry. Besides, the study's focus on US-based VC firms may limit generalizability to other markets. Despite the efforts to establish causality through GIV analysis and the DDD analysis, there may be unobserved factors influencing both network position and performance.

Building on these findings and addressing the gaps identified in the literature review, several avenues for future research emerge. Future research could explore how these network dynamics vary across different sectors or geographies within the VC industry. Additionally, investigating how changes in network centrality translate into tangible benefits for VC firms, such as better deal flow or improved fund performance, would be a valuable extension of this work.

Research examining the relationship between an investor's evolving network position and their ability to attract follow-on investments for portfolio companies could provide valuable insights into the dynamics of VC networks. More detailed analysis of how network position impacts investment performance across different stages of the startup lifecycle – from early-stage to later-stage investments – could yield important practical insights for VC firms.

Examining how international VC relationships differ from domestic ones in terms of network dynamics and influence could provide valuable cross-cultural insights and test the generalizability of the findings. Investigating whether network effects vary across different industry sectors could yield a nuanced understanding of sector-specific dynamics in VC networking. Exploring the interplay between VC networks and founder networks could provide a more holistic view of the entrepreneurial ecosystem.

Longer longitudinal studies tracking the co-evolution of network positions and firm performance over multiple fund cycles could provide insights into long-term network dynamics and the sustainability of network advantages. These future research directions would not only address the gaps in current literature but also deepen the understanding of the complex VC ecosystem.

In conclusion, by revealing the complex dynamics governing VC networks and the importance of timing, success, and relative network positions in shaping a firm's trajectory, this study provides actionable insights for industry participants and policymakers while also opening up rich new avenues for scholarly inquiry. As the venture capital industry continues to evolve and expand globally, understanding and leveraging these network dynamics will be crucial for success and innovation in entrepreneurial finance.

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9 Appendix

9.1 Detailed Variables Description

The data used in this analysis is sourced from the Crunchbase, a highly regarded platform founded by TechCrunch in 2007. Crunchbase data is particularly valued for its reliability, as it provides timestamped information, allowing for precise tracking of network structures. Each investor, organization and individual in the database is uniquely identified by alphanumeric IDs, and the use of trust codes ensures the accuracy of timestamps, covering key events such as company foundations, funding rounds, acquisitions, and IPOs.

The data extraction of the study focused on investments made by US-based investors all around the world between 2010 and 2021. The dataset is then supplemented with detailed information on each investor and organization, including their founding dates, headquarters locations, industry sectors, number of investments, connection reasons, investment types, investment stages, revenue estimates, and employee numbers.

9.1.1 Investor Variables

In the dataset, investors are identified, in turn, as Investor A and Investor B. The variable Connection Reason specifies the type of investment observed for each transaction. For instance, if Investor A invests prior to Investor

B, the Connection Reason is categorized as Early Investor. Conversely, if Investor A invests after Investor B, the Connection Reason is classified as Late Investor. In cases where both investors invest simultaneously, as in a syndicate, the Connection Reason is designated as Same Round.

The locations of the companies involved are represented by the variables Location A and Location B. The variables Investor Type A and Investor Type B categorize the investors based on the types of investments they undertake, while Investor Stage A and Investor Stage B classify the investors according to the stages of investment. The variables Number of Investments A and Number of Investments B reflect the total number of investments made by Investor A and Investor B, respectively. Additionally, the variables Number of Lead Investments A and Number of Lead Investments B indicate the total number of funding rounds led by each investor. The variables Number of Exits (IPO) A and Number of Exits (IPO) B enumerate the IPO exits achieved by the respective investors.

9.1.2 Company Variables

In the dataset, the location of the company is referred to by the variable Headquarters Location. The variable Diversity Dummy is a binary indicator representing the presence of diversity within the company. The variable Estimated Revenue categorizes the company's revenue within specific ranges. The variable Operating Status indicates whether the company is currently active or has ceased operations, while the variable Company Type specifies whether the company operates as a for-profit or non-profit entity. The variable Funding Status outlines the type of transaction the company undergoes. The variable Acquisition Status indicates whether the company has experienced a previous acquisition, and the variable Acquisition Type further classifies the nature of the acquisition. Finally, the variable IPO Status categorizes the company as private, public, or delisted. The variable Industry Groups identifies the industries to which the company belongs. Each company is classified within one or multiple industries under this variable. The variable Funding Type categorizes the round of investments, ranging from Seed to Series A.

9.1.3 K-Shell Variables

The variables ksn_{A_t} and ksn_{B_t} denote the k-shell scores of the investors at time t, while the variables $ksn_{A_{t-1}}$ and $ksn_{B_{t-1}}$ represent the k-shell scores of the investors at time t-1. These variables facilitate tracking changes in k-shell scores over time. To measure and utilize this change, the variables $delta_A$ and $delta_B$ are computed as the difference in k-shell scores between two subsequent periods.

9.2 Data Cleaning Process & Summary Statistics

9.2.1 Industry Groups

The initial dataset encompasses 54 industries. To streamline classification, these industries have been grouped into six logical categories, resulting in a clearer presentation and a more balanced distribution among the groups. Typically, the original Crunchbase classification includes multiple industries for each company. To determine the appropriate logical group for a company, the total number of industries corresponding to each logical group was calculated for each row in the Industry Group column. Companies were then assigned to the logical group with the majority of their industries listed. In cases where a tie occurred between two logical groups, the company was classified into the group with the fewest entries to enhance the dataset's representativeness.

The largest logical group is Finance, Business Services, and Real Estate, which covers industries such as Financial Services, Lending and Investments, Real Estate, Professional Services, Administrative Services, Sales and Marketing, Accounting, Insurance, and Legal Services, totaling 946,476 entries. This is followed by the Consumer, Retail, and Lifestyle group, which merges industries such as Commerce and Shopping, Consumer Goods, Consumer Electronics, Food and Beverage, Clothing and Apparel, Home and Garden, Travel and Tourism, Transportation, Automotive, Community, and Lifestyle, with 873,044 entries. The third largest group is Media, Arts, and Entertainment, including industries such as Media and Entertainment, Music and Audio, Video, Gaming, Sports, Events, Design, Content and Publishing, and Advertising, with a total of 616,258 entries. The Software group, which unites industries such as Software, Apps, Mobile, Platforms, and Artificial Intelligence, has 546,004 entries. Next is the Technology group, which includes industries such as Data and Analytics, Information Technology, Privacy and Security, Hardware, and Internet Services, with 513,420 entries. Finally, the Healthcare, Energy, Education, and Other group comprises a diverse set of industries, including Biotechnology, Healthcare, Science and Engineering, Pharmaceuticals, Medical Devices, Wellness, Energy, Manufacturing, Sustainability, Agriculture and Farming, Natural Resources, Environmental Services, Education, Government and Military, Navigation and Mapping, Nonprofit, Public Safety, and Other, totaling 451,164 entries.

9.2.2 Funding Type

The distribution of the Funding Type variable shows that the majority of observations are of the Series A type, with 1,557,120 observations. This is followed by the Seed type, with 1,456,400 observations, Series B with 1,369,530 observations, and Angel/Pre-Seed with 155,484 observations.

9.2.3 Location Groups

The location variables Location A, Location B (referring to investors), and Headquarters Location (describing companies) are grouped into four main categories of similar sizes to ensure a balanced and stable model, thereby yielding generalizable results. Among the countries represented, all the investors and the majority of companies are from the United States. Consequently, the location variables are divided into four primary groups: San Francisco, California (excluding San Francisco), United States (excluding California and San Francisco), and Rest of the World.

For the Location A and Location B variables, the majority of entries belong to the United States group, with 1,228,650 entries. This is followed by the San Francisco group, with 1048,653 entries, and California with 600,322 entries.

The Headquarters Location variable follows the same grouping sequence. The United States is the majority group, with 1,901,500 entries. The second-largest group is San Francisco, with 1,594,830 entries, followed by California, with 865,796 entries, and finally the Rest of the World group, with 68,264 entries.

9.2.4 Investor Type

The variables Investor Type A and Investor Type B include multiple types of investors in a single entry. Consequently, a hierarchical order has been established, and each entry is classified according to the highest-ranked investor type it contains. The hierarchy, from top to bottom, is as follows: Government Office, Corporate Venture Capital, Venture Capital, Micro VC, Angel

Group, Private Equity Firm, Family Investment Office, Accelerator, Incubator, Fund of Funds, Investment Bank, Co-Working Space, Entrepreneurship Program, Syndicate, Hedge Fund, Pension Fund, Secondary Purchaser, Startup Competition, and University Program. The entries, once modified according to the logical groups, are then grouped into four logical categories: Venture Capital Firms, Institutional Entities, Startup Support Programs, and Investment Funds. The Venture Capital group is the largest, with 2,356,600 entries, including the investor types of Venture Capital and Micro VC. The group with the second-highest number of entries is Institutional Entities, with 178,356 entries, which includes investor types such as Investment Bank, Pension Fund, Government Office, Family Investment Office, Angel Group, Syndicate, and Co-Working Space. This is followed by the Startup Support Programs group, with 134,005 entries, encompassing investor types like Accelerator, Incubator, Entrepreneurship Program, University Program, and Startup Competition. Lastly, the Investment Funds group includes investor types such as Private Equity Firm, Hedge Fund, Fund of Funds, and Secondary Purchaser, with a total of 75,994 entries.

9.2.5 Other Variables

The dataset includes the variable Diversity Spotlight; however, this column only contains entries for companies headquartered in the United States. Given that many companies are composed of employees from diverse ethnic backgrounds, this column can contain numerous entries. Consequently, the Diversity Dummy variable has been created to represent companies with diverse employee backgrounds. This variable takes the value of one if there is at least one ethnicity entry in the Diversity Spotlight variable. In total, 1,306,680 companies are identified as having at least one diverse background.

The variable Estimated Revenue has been rearranged into four categories. The group with the most entries is the 1M to 10M range, with 2,021,400 entries, followed by the 10M to 50M range, with 839,592 entries. The Less than 1M group has 575,010 entries, and the Above 50M group has 476,386 entries.

The variable Acquisition Status is classified into three groups based on whether the company has undergone an acquisition. The primary classifications are Made Acquisitions, with 878,296 entries, Was Acquired, with 803,088 entries, and Both Made Acquisitions and Was Acquired, with 189,188 entries.

The variable Acquisition Type is classified into five groups. The majority group is Acquisition, with 855,148 entries, followed by Merger with 32,376 entries, Acquihire with 26,394 entries, Leveraged Buyout with 10,172 entries, and Management Buyout with 610 entries.

The variable IPO Status is categorized into three groups. The majority group is Private, with 4,207,200 entries. This is followed by the Public group, with 218,608 entries, and the Delisted group, with 4,862 entries.

The means and medians of the variables Number of Investments A and

Number of Investments B are 175 and 90, respectively. The variables Number of Lead Investments A and Number of Lead Investments B have means and medians of 67 and 19, respectively. The means and medians of the variables Number of Exits (IPO) A and Number of Exits (IPO) B are 70 and 22, respectively.

The dataset includes three dummy variables related to the locations of Investors A, B, and the company. The variable $LocationMatch_{AB}$ indicates if the investors are from the same location, $LocationMatch_{AC}$ indicates if Investor A and the Headquarters Location are the same, and $LocationMatch_{BC}$ indicates if Investor B and the Headquarters Location are the same.

The variables $InvestorTypeMatch$ and $InvestorStageMatch$ are binary indicators that return a value of one if the types or stages of Investor A and Investor B are the same, and zero otherwise. The variable IPO_{Dummy} is another binary variable that returns a value of one if the company has undergone an IPO process. Similarly, the variable MA_{Dummy} returns one if the company has been involved in a merger or acquisition (M&A) process. Finally, the variable MA/IPO_{Dummy} returns one if the company has undergone either an IPO or an M&A process.