How do Venture Capitalists become Influential?

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Abstract

I analyse venture capital (VC) firms' progression from peripheral to core network positions using US VC investment data (2010-2021). Through influence estimation and dynamic network analysis, this study examines the three connecting strategies: co-investing with prominent VCs, backing their deals, and receiving their follow-on investments. Using Granular Instrumental Variables and Triple Difference analyses, results indicate that being endorsed by prominent VCs' capital most effectively enhances a firm's influence and financial performance, independent of the success of the portfolio company which brought the investors together.

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1 Introduction

Well-connected venture capitalists (VCs) achieve higher success rates than less-connected investors (Hochberg et al., 2007), yet research has not explored how peripheral investors can ascend to central network positions. Lack of understanding about the advancement of strategic networks creates market inefficiencies and barriers for emerging funds. This is particularly crucial given the role of VCs in driving innovation and economic growth (Lerner and Nanda, 2020; Samila and Sorenson, 2011).

Building on Nahata (2008)'s analysis of lead VC reputation's impact on performance, this study examines how different connection types shape network position and influence. Research shows well-connected VCs outperform less-connected peers in returns, portfolio performance, and fund success (Hochberg et al., 2007; Sorenson and Stuart, 2001). Besides, Ewens et al. (2021) demonstrate how accelerators and platforms have transformed VC-entrepreneur connections. While complementing their work by examining how connections translate to influence, this study focuses on the unexplored mechanisms through which peripheral investors ascend to central network positions.

The study addresses three questions about VC network influence dynamics. First, how do peripheral firms ascend to central positions through: co-investing with influential VCs, backing their deals, or receiving their follow-on investments? Second, how does the effectiveness of these paths vary with investment timing, relative network positions, and investment outcomes? Third, are network position improvements causally driven by connections with influential VCs, rather than unobserved VC quality or strategic anticipation?

This study combines k-shell decomposition with dynamic network modeling. K-shell decomposition stratifies networks by core and periphery, independent of degree centrality, quantifying node influence (Kitsak et al., 2010), and it has been widely applied in several (Makse and Zava, 2024) fields, as election prediction through the propagation of fake news. Applied to VC networks by Li et al. (2023), this method captures both connection quantity and strategic value, better reflecting information and opportunity flow than traditional centrality measures.

Building on Li et al. (2023)'s causal network-performance findings, I analyze US VC institutions' temporal co-investment networks monthly, capturing complex patterns like burstiness, memory effects, and non-stationarity undetectable by in static analyses. I examine how different connection types affect movement to central positions by analyzing three paths to connect with core VCs:

1. Syndicate: co-investing alongside influential VCs
2. Backing: providing follow-on funding to their portfolio companies
3. Endorsement: receiving their follow-on funding in portfolio companies

I employ Granular Instrumental Variables (GIV) following Gabaix and Koijen (2024) to establish causality. The method exploits exogenous variations in connection opportunities arising from VC deals' multi-party nature. For each VC firm, I construct granular instruments measuring connections to influential VCs across investment stages, weighted by the deviation from expected connections given firm characteristics. Using demeaned instruments, the analysis reveals causal impacts of influential VC connections on network position, particularly in endorsement investments.

I employ triple difference (DDD) analysis to examine connection details, leveraging temporal sequences and relative VC positions. The treatment group comprises VCs connecting to higher k-shell firms, while the control group includes non-connecting firms. The analysis considers connection type, connected investor's influence, and k-shell differences between investors, with portfolio company success as an additional dimension.

I find that receiving follow-on investments from influential VCs most effectively drives network ascension, independent of portfolio company outcomes. This suggests investment validation by core VCs outweighs financial performance in determining network influence.

The study's theoretical model demonstrates how connection types asymmetrically affect influence, with early-stage validation from prominent VCs yielding the highest returns. The model explains how initial network advantages create persistent performance differences through state and path dependence, predicting influence accumulation patterns based on timing and partner characteristics. This framework links the centrality of the network with the creation of economic value in venture capital. For VC firms, particularly early-stage investors, attracting follow-on investments from core VCs proves to be more crucial to gaining influence than exit success rates.

This research advances three streams of literature: VC network centrality and performance (Hochberg et al., 2007; Sorenson and Stuart, 2001) by establishing causal evidence through GIV and DDD analysis; dynamic network analysis in financial markets (Di Maggio et al., 2019) by capturing temporal patterns in VC networks; and k-shell decomposition (Kitsak et al., 2010; Li et al., 2023) by applying it to VC syndication networks. It extends research on entrepreneurial ecosystems (Hsu, 2004; Bygrave, 1987) by identifying specific paths to network centrality.

Section 2 reviews relevant literature. Section 3 details data and methodology, including dynamic network construction and k-shell decomposition. Section 4 presents

GIV and DDD analysis results. Section 5 discusses implications for VC stakeholders. Section 6 concludes with contributions, limitations, and future research directions.

2 Literature Review

Network centrality's role in VC performance was established by Hochberg et al. (2007), who demonstrated that better-connected VCs achieve higher portfolio exit rates. Building on this, Hochberg et al. (2010) showed how dense VC networks create entry barriers, protecting incumbents while challenging newcomers.

Initially, Lerner (1994) found established VCs co-invest with peers in early rounds but include less established firms later, while Nahata (2019) showed reputable VCs form more selective, compact syndicates, demonstrating how reputation shapes syndicate structure. Hochberg et al. (2015) shows how difficult entering a closed group is. Further Sorenson and Stuart (2001) studied how syndication networks enable VCs to expand geographically by leveraging local partners' expertise. Gu et al. (2019) showed structural embeddedness, rather than relational ties, primarily shapes VC networks, emphasizing shared interests over personal relationships.

On a similar note, Bellavitis et al. (2017) showed network position benefits vary with firms' resource endowment. Zhelyazkov and Gulati (2016) revealed how failed partnerships damage network positions, highlighting the role of the reputation. Garfinkel et al. (2024) showed how alumni networks influence VC financing decisions, while Howell and Nanda (2023) revealed gender-based differences in networking effects. These findings demonstrate how institutional ties and personal characteristics shape network outcomes.

Under a mthodological perspective, beyond traditional degree centrality, k-shell decomposition better identifies influential network nodes Kitsak et al. (2010). Applied to VC networks, Li et al. (2023) used this method to reveal distinct VC groups with varying growth trajectories, demonstrating network position's link to performance. Further, moving beyond static analysis, Zava and Caselli (2024) developed a dynamic bipartite network model that captures temporal patterns in VC investments, including burstiness, memory effects, and nonstationarity across funding stages.

Key questions remain unexplored: how peripheral investors gain network centrality, the relative impact of different networking strategies, and how network position influences performance across investment stages. This study addresses these gaps by combining k-shell decomposition with dynamic network modeling to analyze influence acquisition and its relationship with investment performance.

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 the 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 endorsement connections with 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 a 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 the evaluation of policies to improve market outcomes by affecting the costs or benefits of network formation. 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 the position of the network creates economic value, why timing matters in network formation, how the influence accumulates dynamically, what determines the equilibrium structure of the network, and how the effects of the network 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

I analyze VC influence through multiple approaches, constructing a dynamic co-investment network that captures temporal patterns. K-shell decomposition measures strategic network positioning beyond connection count, distinguishing influential VCs from merely well-connected ones. Then I employ Granular Instrumental Variables (GIV) analysis to establish causality between connections and influence by using unexpected VC connections as natural experiments. The results show that follow-on investments from influential VCs more effectively drive network position gains.

Further, I use Triple Difference (DDD) analysis to examine how connection type, initial network positions, and partner influence affect network ascension. This granular approach confirms follow-on investments from influential VCs most effectively drive influence gains, independent of portfolio company outcomes, while demonstrating timing and partner choice significance. Robustness checks rule out anticipatory connections, confirm results hold for indirect connections, and show findings are not driven by high-quality VCs naturally attracting more connections.

These complementary analyses establish causality in network influence gains, identify effective strategies for building influence, and show validation through follow-on investment outweighs co-investment effects. Results remain robust across methods and checks.

4.1 Data

The data comes from Crunchbase.com's academic API (2010-2021), a comprehensive startup database founded by TechCrunch in 2007. The platform combines manual contributor entries with verified web-crawler data on funding rounds, IPOs, and acquisitions. The sample includes companies founded between 2010-2017 with at least one US-based investor. For each organization, data covers foundation dates, locations, industries, revenue ranges, employee counts, funding rounds, exits, and deal participants, including financial organizations and general partners.

For investors, data includes founding dates, investment metrics (total investments, led deals, exits), expertise stage, location, and portfolio details. For individual investors, additional data covers gender, career history, social media, and education, all sourced from Crunchbase sections. Data cleaning removed inconsistent entries based on Crunchbase's trust code value, using a self-penalizing strategy to ensure validity.

The dataset covers VC firm and portfolio company identifiers, investment details (dates, amounts, rounds), exit events, and sectors. Analysis includes VCs with minimum 5 investments. Tables 1 summarizes VC characteristics and investment stages, Tables 2 and 3 show portfolio company distribution by geography and industry, and Table 4 details sample construction. The appendix provides complete variable descriptions.

To assess whether Crunchbase's coverage has remained stable over time, I compare the venture capital investment figures it reports for the United States with those provided by the National Venture Capital Association (NVCA), which serves as a widely recognized benchmark for industry trends. A consistent ratio between Crunchbase-reported volumes and NVCA-reported figures across years would suggest that Crunchbase's data coverage has remained proportional to the overall industry, rather than expanding or contracting in a way that could bias the observed network dynamics. Historical comparisons indicate that the share of venture capital investment captured by Crunchbase relative to NVCA figures remains relatively stable, reinforcing the reliability of the results and mitigating concerns that improved data collection over time could be driving the findings.

Nevertheless, as private deals are not under disclosure requirements, firms that prefer to operate discreetly, particularly those investing in niche markets or engaging in proprietary deal flows, may be underrepresented. This selection bias could potentially affect the estimated relationships if the network centrality of disclosed investments systematically differs from that of undisclosed transactions. If more established or highly networked VCs are more likely to report their deals, the results could overstate the role of influential connections in driving centrality changes. However, if disclosure is random with respect to network position, then selection bias is less of a concern. To mitigate this issue, I restrict the analysis to venture capital firms that are observed consistently over time and conduct robustness tests that compare firms with high and low disclosure frequencies to assess whether reporting patterns influence the findings. These tests suggest that while selection effects may be present, they are unlikely to drive the core results, reinforcing the validity of the observed network dynamics.

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
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%

4.2 Network Construction

The dynamic network connects VCs through shared portfolio companies, updating monthly from 2010-2021. While building on Nahata (2008)'s insights on VC reputation dynamics, this study employs k-shell decomposition rather than IPO market share to measure centrality. Monthly updates capture temporal patterns includ-

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 VC firms	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.

ing burstiness (uneven deal flow), memory effects (past states influencing future connections), and non-stationarity (structural changes across funding stages).

4.3 K-shell Decomposition

K-shell decomposition measures node centrality by considering neighbors' connectivity, providing more nuance than degree centrality. The decomposition process:

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 until all nodes are assigned

This process runs monthly to track VCs' k-shell values over time. Figure 1 illustrates the decomposition process with a simple network divided into three shells (k=1,2,3). Yellow nodes have degree one, green nodes degree two, and purple nodes degree three. Nodes No.5 and No.6 demonstrate how k-shell differs from degree centrality. Despite both having degree 7, No.5 belongs to k=1 shell as its connections become isolated during decomposition, while No.6 maintains three stable connections until k=3, placing it in the 3-shell.

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

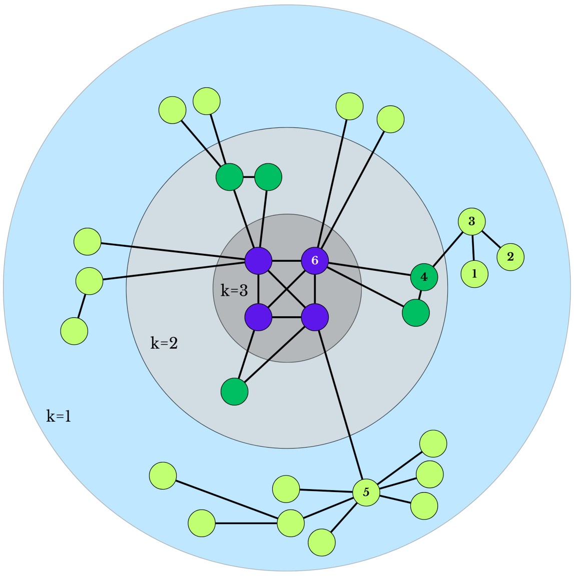

Figure 1: **K-shell decomposition of a network.** Nodes are assigned to shells (k=1 yellow, k=2 green, k=3 purple) based on their connectivity. The process removes nodes iteratively, starting with the least connected. Nodes 5 and 6 illustrate how same-degree nodes can belong to different shells, demonstrating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

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 syndication, where a peripheral investor participates in a deal 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 endorsement, or 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 endorsement 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.

4.5 K-shell and success

Panel regression analysis confirms Li et al. (2023)'s findings that k-shell position positively correlates with success metrics (exits, follow-on funding, unicorn creation) in the US market, as shown in Table 5. The study's core analyses use Granular Instrumental Variables and Triple Differences to establish causality between network position and investment performance.

4.6 GIV: Granular Instrumental Variables Approach

The Granular Instrumental Variables (GIV) approach, following Gabaix and Koijen (2024), exploits idiosyncratic variation in influential VC connections while addressing endogeneity. Using k-shell value as the dependent variable, I analyze the three connection types: syndication, backing, and endorsement. Influential VCs are defined as those in the top 10% of k-shell values at time t.

Next, I construct granular instruments for each VC firm i. I create three instruments: $G_{endorsement_i}$, the sum of endorsement connections; $G_{backing_i}$, the sum of backing connections; and $G_{syndicate_i}$, the sum of syndication connections. 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 (endorsement, backing, syndication) to an influential VC, and $E[z_{ij}]$ is the expected number of such connections.

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

$$\begin{aligned}\Delta Kshell_i = \alpha + \beta_{endorsement} \cdot G_{endorsement_i} + \beta_{backing} \cdot G_{backing_i} \\ + \beta_{syndicate} \cdot G_{syndicate_i} + \gamma \cdot X_i + \Delta\varepsilon_i\end{aligned} \tag{7}$$

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 VC 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 $j \in \{endorsement, backing, syndication\}$.

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

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

The GIV approach estimates direct connection effects while mitigating endogeneity through idiosyncratic variation. Valid causal estimates require instruments based on idiosyncratic connection components: $(z_{ij} - E[z_{ij}])$, where z_{ij} is the actual connection and $E[z_{ij}]$ the expected connection based on observables.

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:

$$\begin{aligned} Cov((z_{ij} - E[z_{ij}]), X_i) = 0 \\ Cov((z_{ij} - E[z_{ij}]), X_j) = 0 \\ Cov((z_{ij} - E[z_{ij}]), B_i) = 0 \\ Cov((z_{ij} - E[z_{ij}]), B_j) = 0 \end{aligned} \tag{10}$$

Unexpected connection deviations arise from exogenous factors: deal timing constraints, market conditions, portfolio company preferences, and geographic coincidences. The multi-party nature of VC deals further ensures connection patterns aren't solely determined by bilateral VC characteristics. VC-level clustered standard errors account for serial correlation, with controls for firm characteristics and year fixed effects.

4.7 DDD: Triple Interaction Difference-in-Differences Model

Analysis uses individual VC connections as observation units, measuring frequency and intensity over time (2010-2021) to track network position changes. The Triple Difference (DDD) analysis examines three dimensions:

1. Connection type ($C_{(AB),t}$): endorsement (baseline), backing, or syndication investments

2. Relative network position ($\Delta Ks_{(AB),(t-1)}$): k-shell value difference between VCs before connection

3. Connected VC's influence ($I_{B,(t-1)}$): whether connected VC is in top 10% of k-shell values

The main model specification is as follows:

$$\begin{aligned}
\Delta Ks_{A,(t-1,t)} &= \beta_0 + \beta_1(C_{(AB),t}) \\
&+ \beta_2(Ks_{(A),(t-1)} - Ks_{(B),(t-1)}) + \beta_3(I_{B,(t-1)}) \\
&+ \beta_4(C_{(AB),t} * (Ks_{(A),(t-1)} - Ks_{(B),(t-1)})) + \beta_5(C_{(AB),t} * I_{B,(t-1)}) \\
&+ \beta_6(I_{B,(t-1)} * (Ks_{(A),(t-1)} - Ks_{(B),(t-1)})) \\
&+ \beta_7(C_{(AB),t} * I_{B,(t-1)} * (Ks_{(A),(t-1)} - Ks_{(B),(t-1)})) \\
&+ \gamma X_{A_t} + \theta X_{B_t} + \tau_{c_{AB}} + \varepsilon_{it}
\end{aligned} \tag{11}$$

Where:

- $\Delta Ks_{A,(t-1,t)}$ 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.

- $I_{B,(t-1)}$ 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.

- $C_{(AB),t}$ is a dummy variable indicating the type of connection (endorsement, backing, syndication) that occurred between VC firms A and B at time t. It is the additional dimension of the DDD model.

- $(Ks_{(A),(t-1)} - Ks_{(B),(t-1)})$ 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.

The model examines how connection events affect VC influence (K-shell value) through main effects and interactions: Main effects β_1, β_2, and β_3 capture individual impacts of connection events, network position differences, and connected firm's influence. Two-way interactions examine:

- β_4: $C_{(AB),t} * \Delta Ks_{AB,(t-1)}$ - connection impact by network position gap

- β_5: $C_{(AB),t} * I_{B,(t-1)}$ - connection impact by partner influence

- β_6: $I_{B,(t-1)} * (Ks_{(A),(t-1)} - Ks_{(B),(t-1)})$ - influential partner impact by position gap

The triple interaction β_7 $(C_{(AB),t} * I_{B,(t-1)} * (Ks_{(A),(t-1)} - Ks_{(B),(t-1)}))$ shows how connection effects vary with both position gap and partner influence. Controls (γ, θ, τ) account for firm characteristics and time-invariant factors.

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:

$$
\begin{aligned}
\Delta Ks_{A,(t-1,t)} = {} & \beta_0 + \beta_1(C_{(AB),t}) \\
& + \beta_2(Ks_{(A),(t-1)} - Ks_{(B),(t-1)}) + \beta_3(I_{B,(t-1)}) + \beta_4(S_c) \\
& + \beta_5(C_{(AB),t} * (Ks_{(A),(t-1)} - Ks_{(B),(t-1)})) \\
& + \beta_6(C_{(AB),t} * I_{B,(t-1)}) + \beta_7(I_{B,(t-1)} * (Ks_{(A),(t-1)} - Ks_{(B),(t-1)})) \\
& + \beta_8(C_{(AB),t} * S_c) + \beta_9(I_{B,(t-1)} * S_c) + \beta_{10}((Ks_{(A),(t-1)} - Ks_{(B),(t-1)}) * S_c) \\
& + \beta_{11}(C_{AB,t} * I_{B,(t-1)} * (Ks_{(A),(t-1)} - Ks_{(B),(t-1)})) + \beta_{12}(C_{(AB),t} * I_{B,(t-1)} * S_c) \\
& + \beta_{13}(C_{(AB),t} * S_c * (Ks_{(A),(t-1)} - Ks_{(B),(t-1)})) \\
& + \beta_{14}(S_c * I_{B,(t-1)} * (Ks_{(A),(t-1)} - Ks_{(B),(t-1)})) \\
& + \beta_{15}(C_{(AB),t} * S_c * I_{B,(t-1)} * (Ks_{(A),(t-1)} - Ks_{(B),(t-1)})) \\
& + \gamma X_{A_t} + \theta X_{B_t} + \omega_{c_{AB}} + \varepsilon_{it}
\end{aligned} \tag{12}
$$

The extended model adds investment success effects through additional interactions: Main effect β_4 captures connecting company's success impact on network centrality. New two-way interactions:

- β_8: $C_{(AB),t} * S_c$ - connection impact by investment success
- β_9: $I_{B,(t-1)} * S_c$ - influential partner impact by success
- β_{10}: $(Ks_{(A),(t-1)} - Ks_{(B),(t-1)}) * S_c$ - position gap impact by success

Three-way interactions:

- β_{12}: $C_{(AB),t} * I_{B,(t-1)} * S_c$ - connection type by influence and success

- β_{13}: $C_{(AB),t} * S_c * (Ks_{(A),(t-1)} - Ks_{(B),(t-1)})$ - connection type by success and position gap
- β_{14}: $S_c * I_{B,(t-1)} * (Ks_{(A),(t-1)} - Ks_{(B),(t-1)})$ - success by influence and position gap

Four-way interaction β_{15} $(C_{(AB),t} * S_c * I_{B,(t-1)} * (Ks_{(A),(t-1)} - Ks_{(B),(t-1)}))$ examines how all factors jointly affect centrality changes. In this specification, company fixed effects τ are replaced with controls $\omega_{c_{AB}}$ to accommodate the S_c variable.

A key requirement for the validity of the Triple Difference (DDD) analysis is that the parallel trends assumption holds, meaning that before the treatment (i.e., forming a connection with an influential VC), the network position (measured by k-shell values) of treated and control firms should be evolving similarly. To validate this assumption, I run a pre-trend regression, estimating the effect of a future connection on k-shell values. The results and discussion are available in the appendix. The coefficient on this placebo treatment is statistically insignificant, suggesting that firms on track to receive influential backing do not exhibit systematically different network dynamics before the connection occurs. This supports the claim that the estimated effects in our DDD model are not driven by pre-existing trends but rather by the influence of the network connection itself.

4.8 Robustness

To strengthen the validity of findings and address potential endogeneity concerns, I conduct three robustness checks. First, I examine anticipatory connections to rule out strategic positioning effects. Second, I analyze indirect connections to verify that results hold beyond direct relationships. Third, I investigate high-potential investors to ensure findings are not driven by unobserved VC quality. These checks provide complementary evidence for the causal relationship between network position and VC performance.

Anticipatory Connections The anticipatory connections analysis examines reverse causality by studying VCs before they become influential (top 10% k-shell values). For VCs transitioning to influential status, I analyze their connections in the three preceding months. The DDD analysis is replicated using these pre-influence connections instead of established influential connections. If main results reflect causal effects, anticipatory connections should show minimal impact.

The model replaces $I_{B,(t-1)}$ with a dummy variable indicating VC B's upcoming influential status, maintaining all other specifications. This comparison helps establish causality and rule out anticipation effects.

Indirect Connections The indirect connections analysis examines network effects through mutual third-party connections, providing more exogenous variation in network structure. I analyze cases where unconnected VCs (A and B) become linked when a mutual connection (D) becomes influential, focusing on pairs without prior mutual connections. The methodology follows these steps: a) identify VCs becoming influential (top 10% k-shell values); b) for each new influential VC (D), find VC pairs (A and B) connected to D but not each other; c) treat D's connection to both as an exogenous shock linking A and B; d) analyze resulting changes in A and B's network positions

The model follows equation 7, with Connection Type defined as Endorsement (A connected to D before B) or Backing (B before A). Syndication connections are excluded as they imply direct A-B links through syndication. This approach addresses selection bias and homophily concerns by examining connections formed through third-party actions rather than direct strategic choices.

High-Potential Investors The high-potential investors analysis addresses reverse causality concerns that strong firms naturally attract influential VCs. Using lead-lag analysis, I test whether future influential connections predict current network position changes. The absence of such prediction would support the causal interpretation.

I estimate the following model:

$$\Delta Kshell_{i,t} = \alpha + \sum_{k=-2}^{2} \beta_k \cdot G_{i,t+k} + \gamma \cdot X_{i,t} + \delta_t + \varepsilon_{i,t} \tag{13}$$

In the model, $\Delta Kshell_{i,t}$ represents firm i's k-shell value change at time t, $G_{i,t+k}$ is the granular instrument for influential VC connections at $t+k$, $X_{i,t}$ contains investor-specific variables, and δ_t are time fixed effects. The model includes two leads ($k = 1, 2$) and two lags ($k = -2, -1$) of the granular instrument, with contemporaneous effect ($k = 0$). Lead terms (β_1, β_2) test for reverse causality, while contemporaneous (β_0) and lag terms (β_{-1}, β_{-2}) measure connection effects. Significant effects only in contemporaneous and lag terms would support the causal interpretation.

5 Results

The results examine four key aspects: the relationship between k-shell position and investment performance, paths to network centrality, network evolution patterns, and position impact across funding stages. GIV and Triple Difference analyses reveal how connection timing and success outcomes affect network centrality.

5.1 K-shell Position and Investment Performance

K-shell position strongly correlates with investment performance across all success metrics. VCs in the top k-shell (top 10%) achieve 28.3% exit rates, compared to 18.7% for middle k-shells (10-25%) and 7.1% for lowest k-shells (bottom 75%). Table 5 shows normalized k-shell position as the strongest success predictor, with particularly strong effects on unicorn creation (21.56%), follow-on funding (15.83%), and exit rates (10.52%), all significant at 1%. Firm age demonstrates positive effects on exit rates (0.17%, $p < 0.05$) and follow-on funding (0.25%, $p < 0.05$), though its impact on unicorn creation remains statistically insignificant.

Geographic focus on California exhibits significant positive effects across all metrics (Exit Rate: 1.82%, Follow-on Funding: 2.10%, Unicorn Creation: 1.28%; all $p < 0.001$). Industry specialization shows moderate benefits (Exit Rate: 0.94%, Follow-on Funding: 1.08%, Unicorn Creation: 0.67%; all $p < 0.01$), while R&D-intensive focus enhances performance significantly (Exit Rate: 1.45%, Follow-on Funding: 1.72%, Unicorn Creation: 1.03%; all $p < 0.001$). The analysis of follow-on funding reveals that portfolio companies of VCs in higher k-shells secure additional capital more frequently. The probability of raising a subsequent round within 18 months reaches 62.4% for top k-shell firms, 48.9% for middle k-shells, and 15.2% for low k-shells.

The results provide evidence for the importance of network position in determining VC firm performance. My findings extend the work of Hochberg et al. (2007), and apply Li et al. (2023)'s analysis to my US-based dataset.

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.

5.2 Paths to Central Network Positions

The analysis of 3.8 million dyadic connections reveals three paths to network centrality, with 30.6% involving influential VCs. The paths and their impacts on scaled k-shell value (0-100) over 12 months are:

1. Syndicating with influential VCs: 53% of instances, yielding a 5-point increase
2. Backing investments of influential VCs: 31% of instances, yielding a 2.5-point increase
3. Having own investments backed by influential VCs: 16% of instances, yielding an 8-point increase

Table 6 details these paths' frequencies and impacts. Notably, receiving follow-on investments from influential VCs, while least common, generates the strongest network position gains. This finding aligns with Triple Difference (DDD) results on connection timing effects, suggesting that validation from established VCs particularly enhances network centrality.

Investment Strategy	**% of Obs.**	**No. of Obs.**	**K-shell Increase**
Having own investments backed by influential VCs	16%	608,635	8.0
Co-investing with influential VCs	53%	2,016,097	5.0
Backing investments of influential VCs	31%	1,179,222	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.

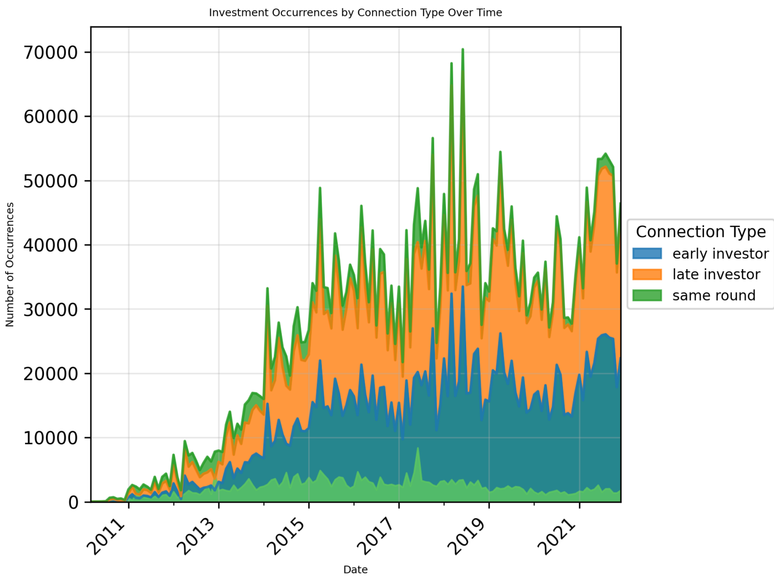

Figure 2: **Investment occurrences by connection type** from 2011 to 2022. The chart demonstrates significant burstiness in VC investment activities (burstiness coefficient: 0.6941), with distinct periods of high activity and relative quiet across endorsement, backing, and syndication investments.

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 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

	Syndication	Endorsement	Backing
Syndication	0.2849	0.2930	0.2965
Endorsement	0.0815	0.1398	0.0352
Backing	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 Granular Instrumental Variables (GIV) analysis of influential VC connections' impact on network position, measured by k-shell value changes (Δ K-shell). Specification (1) shows significant positive effects of all connection types on network position. Endorsement connections ($G_{endorsement}$) produce the greatest impact (15. 6%, p $<$ 0.01), followed by the syndication connections ($G_{syndication}$, 11.8%, p $<$ 0.01) and backing connections ($G_{backing}$, 9.2%, p $<$ 0.05).

Specification (2) validates the GIV approach through a non-influential connection test. Connections to non-influential VCs ($G_{noninfluential}$) show no significant effect (1.2%, not significant), confirming that observed effects stem from influential VC connections. Specification (3) reveals heterogeneous effects across firm sizes. While main effects remain significant, negative interaction terms ($G_{endorsement} \times Size$, -0.018%, p $<$ 0.05) indicate smaller firms benefit more from influential connections, particularly in early-stage investments. These results establish that connections to

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
$G_{endorse}$	0.156***		0.214***
	(0.035)		(0.052)
$G_{backing}$	0.092**		0.128**
	(0.033)		(0.049)
$G_{syndicate}$	0.118***		0.172***
	(0.034)		(0.051)
$G_{noninfl}$		0.012	
		(0.025)	
$G_{endorse} \times$ Size			-0.00018**
			(0.00007)
$G_{backing} \times$ Size			-0.00009
			(0.00006)
$G_{syndicate} \times$ 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

influential VCs, especially those initiated by them, significantly enhance network position, with stronger effects for smaller firms.

5.5 DDD: Triple Difference Analysis

Table 9: Triple Difference Models Results

Effect Type	**Coefficient**	**Std. Error**
Main Effects		
Intercept (β_0)	0.0124***	(0.0018)
$\mathrm{C}_{(AB),t}$: backing (β_1)	-0.0646***	(0.0082)
$\mathrm{C}_{(AB),t}$: syndication (β_1)	-0.0380***	(0.0079)
$\Delta K\mathrm{s}_{(AB),(t-1)}$ (β_2)	0.5760***	(0.0234)
$\mathrm{I}_{B,(t-1)}$ (β_3)	0.1830***	(0.0156)
Two-Way Interactions		
$\mathrm{C}_{(AB),t}$: backing $\times \Delta K\mathrm{s}_{(AB),(t-1)}$ (β_5)	-0.1350***	(0.0312)
$\mathrm{C}_{(AB),t}$: syndication $\times \Delta K\mathrm{s}_{(AB),(t-1)}$ (β_5)	-0.0940***	(0.0298)
$\mathrm{C}_{(AB),t}$: backing $\times$ $\mathrm{I}_{B,(t-1)}$ (β_6)	-0.0520***	(0.0187)
$\mathrm{C}_{(AB),t}$: syndication $\times$ $\mathrm{I}_{B,(t-1)}$ (β_6)	-0.0310*	(0.0179)
$\mathrm{I}_{B,(t-1)}$ $\times \Delta K\mathrm{s}_{(AB),(t-1)}$ (β_7)	0.0890**	(0.0356)
Three-Way Interactions		
$\mathrm{C}_{(AB),t}$: backing $\times$ $\mathrm{I}_{B,(t-1)}$ $\times \Delta K\mathrm{s}_{(AB),(t-1)}$ (β_{11})	0.0210***	(0.0052)
$\mathrm{C}_{(AB),t}$: syndication $\times$ $\mathrm{I}_{B,(t-1)}$ $\times \Delta K\mathrm{s}_{(AB),(t-1)}$	0.0135***	(0.0049)
Controls and Model Fit		
Controls inv A	Yes	
Controls inv B	Yes	
Fixed Effects Company	Yes	
Observation Number	3,803,954	
R squared	26.3%	
Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$		

Tables 9 and 10 presents Triple Difference (DDD) analysis results across two specifications, examining how connections, network positions, and investment outcomes affect VC network centrality.

Table 9 shows that, compared to endorsement connections, backing and syndication connections negatively impact K-shell value changes (-6.46% and -3.80%, p < 0.01).

Table 10: Success Effects on Network Position

Effect Type	**Coefficient**	**Std. Error**
Main Effect		
Success_c	0.0069*	(0.0027)
Two-Way Interactions		
$\text{Success}_c \times$ Backing	0.0020*	(0.0015)
$\text{Success}_c \times$ Syndication	0.0030**	(0.0014)
$\text{Success}_c \times \text{I}_{B,(t-1)}$	0.0015	(0.0018)
$\text{Success}_c \times \Delta K\text{s}_{(AB),(t-1)}$	0.0010*	(0.0025)
Three-Way Interactions		
$\text{Success}_c \times$ Backing $\times \text{I}_{B,(t-1)}$	0.0005	(0.0020)
$\text{Success}_c \times$ Syndication $\times \text{I}_{B,(t-1)}$	0.0008	(0.0019)
$\text{Success}_c \times$ Backing $\times \Delta K\text{s}_{(AB),(t-1)}$	0.0012**	(0.0022)
$\text{Success}_c \times$ Syndication $\times \Delta K\text{s}_{(AB),(t-1)}$	0.0018*	(0.0021)
$\text{Success}_c \times \text{I}_{B,(t-1)} \times \Delta K\text{s}_{(AB),(t-1)}$	0.0007	(0.0023)
Four-Way Interactions		
$\text{Success}_c \times$ Backing $\times \text{I}_{B,(t-1)} \times \Delta K\text{s}_{(AB),(t-1)}$	0.0003**	(0.0025)
$\text{Success}_c \times$ Syndication $\times \text{I}_{B,(t-1)} \times \Delta K\text{s}_{(AB),(t-1)}$	0.0004*	(0.0024)
Controls and Model Fit		
Controls inv A	Yes	
Controls inv B	Yes	
Controls Company	Yes	
Observation Number	3,803,954	
R squared	26.4%	
Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$		

The initial network position difference ($\Delta Kshell_{(AB),(t-1)}$) strongly influences centrality (57.60%, p < 0.01), as does the connection with influential firms (18.30%, p < 0.01).

Interaction effects reveal that backing/syndication connections reduce the benefit of initial network position differences (13.50% and -9.40%, p < 0.01). However, three-way interactions show that influential connections mitigate this negative effect (2.10% and 1.35%, p < 0.01), particularly for firms with higher initial positions.

Table 10 incorporates investment success, showing minimal direct effect on centrality (0.69%, p < 0.10). Success interactions with connection types yield small positive effects for syndication (0.30%, $p < 0.05$) and backing connections (0.20%, $p < 0.10$). Four-way interactions demonstrate negligible positive effects (0.04% and 0.03%, $p < 0.10$ and $p < 0.05$ respectively).

6 Robustness

The robustness analysis examines anticipatory connections, indirect connections, and high-potential investors to address potential endogeneity and causality concerns in the main findings.

6.1 Anticipatory connections

The anticipatory connections analysis examines pre-influence connections formed three months before VCs enter the top 10% of k-shell values. This approach identifies VCs that transition to influential status during the study period and analyzes their connections immediately preceding this transition. By comparing these anticipatory connections to actual influential connections, this test helps establish whether observed effects stem from influential status rather than anticipation or other factors. Replicating the main analysis with anticipatory connections provides a crucial test of causality. If the primary results reflect causal effects of influential connections, anticipatory connections should show minimal impact on network position changes. Conversely, similar effects from anticipatory connections would suggest the results might be driven by unobserved factors or strategic anticipation.

Table 11 compares anticipatory connection tests with main results. In the anticipatory model, Connection (Backing) and Connection (Syndication) coefficients lose statistical significance and show substantially reduced magnitudes. Similarly, the

Table 11: 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 (Backing)	-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 (Backing) $\times$ $\Delta Kshell_{AB,(t-1)}$	-0.1350***	-0.0287
	(0.0312)	(0.0356)
Connection (Syndication) $\times$ $\Delta Kshell_{AB,(t-1)}$	-0.0940***	-0.0195
	(0.0298)	(0.0339)
Connection (Backing) $\times$ $Influence_{B,(t-1)}$	-0.0520***	-0.0103
	(0.0187)	(0.0213)
Connection (Syndication) $\times$ $Influence_{B,(t-1)}$	-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 (Backing) $\times$ $Influence_{B,(t-1)}$ $\times$	0.0210***	0.0042
$\Delta Kshell_{AB,(t-1)}$	(0.0052)	(0.0059)
Connection (Syndication) $\times$ $Influence_{B,(t-1)}$ $\times$	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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

$Influence_{B,(t-1)}$ coefficient decreases markedly (2.15%, not significant) compared to the main model (18.30%, p ¡ 0.01). Interaction terms in the anticipatory model also lose significance and magnitude, indicating the relationship between connection types, influence, and network positions exists only with established influential VCs. Only $\Delta Kshell_{AB,(t-1)}$ maintains similar significance and magnitude across both models, suggesting network position differences affect outcomes independently of connected VC's influence status. These results support a causal interpretation: network influence changes stem from connections with already-influential VCs rather than anticipation effects or connections with soon-to-be-influential VCs.

6.2 Indirect Connections

The indirect connections model confirms the main findings while revealing smaller effect magnitudes. Backing connections maintain their negative impact on ΔKshell, though with reduced coefficients. Similarly, influential VC connections ($Influence_{B,(t-1)}$) show positive but decreased effects (14.25% vs 18.30% in the main model). Interaction effects between $Influence_{B,(t-1)}$ and $\Delta \text{Kshell}_{(AB),(t-1)}$ retain significance and direction but demonstrate smaller magnitudes. The model's lower R-squared value (22.8% vs 26.3%) indicates reduced explanatory power compared to direct connections. These results, observed in more plausibly exogenous connection scenarios, support the robustness of the main findings and demonstrate that network influence effects persist beyond direct strategic connections.

6.3 High-Potential Investors

Table 13 presents the lead-lag analysis examining potential reverse causality between influential VC connections and network position changes. The contemporaneous

Table 12: 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)
$C_{(AB),t}$: backing (β_1)	-0.0646***	-0.0312***
	(0.0082)	(0.0090)
$C_{(AB),t}$: syndication (β_1)	-0.0380***	
	(0.0079)	
$\Delta Ks_{(AB),(t-1)}$ (β_2)	0.5760***	0.4982***
	(0.0234)	(0.0256)
$I_{B,(t-1)}$ (β_3)	0.1830***	0.1425***
	(0.0156)	(0.0171)
$C_{(AB),t}$: backing $\times$ $\Delta Ks_{(AB),(t-1)}$ (β_5)	-0.1350***	-0.0845**
	(0.0312)	(0.0342)
$C_{(AB),t}$: syndication $\times$ $\Delta Ks_{(AB),(t-1)}$ (β_5)	-0.0940***	-0.0578*
	(0.0298)	(0.0327)
$C_{(AB),t}$: backing $\times$ $I_{B,(t-1)}$ (β_6)	-0.0520***	-0.0312*
	(0.0187)	(0.0205)
$C_{(AB),t}$: syndication $\times$ $I_{B,(t-1)}$ (β_6)	-0.0310*	-0.0185
	(0.0179)	(0.0196)
$I_{B,(t-1)} \times \Delta Ks_{(AB),(t-1)}$ (β_7)	0.0890**	0.0678*
	(0.0356)	(0.0390)
$C_{(AB),t}$: backing $\times$ $I_{B,(t-1)}$	0.0210***	0.0156**
$\times \Delta Ks_{(AB),(t-1)}$ (β_{11})	(0.0052)	(0.0057)
$C_{(AB),t}$: syndication $\times$ $I_{B,(t-1)}$	0.0135***	0.0098**
$\times \Delta Ks_{(AB),(t-1)}$ (β_{11})	(0.0049)	(0.0054)
Observations	3,803,954	2,987,623
R-squared	26.3%	22.8%

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

Table 13: 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

effect (G_t) remains significant (14.2%, $p < 0.01$), while lead terms (G_{t+1}, G_{t+2}) show insignificant effects (3.2%, 1.5%). Lag terms (G_{t-1}, G_{t-2}) demonstrate declining but significant positive effects (8.9%, $p < 0.05$; 5.6%, $p < 0.10$), suggesting persistent impact of influential connections. Firm size maintains its positive effect (0.11%, $p < 0.01$). The absence of significant lead effects, combined with strong contemporaneous and declining lag effects, supports a causal interpretation: network position changes result from influential VC connections rather than unobserved firm characteristics attracting such connections.

7 Discussion and Implications

The Power of Network Position The relationship between k-shell position and investment performance extends beyond traditional degree centrality measures studied by Hochberg et al. (2007), revealing the importance of higher-order network structures. K-shell decomposition captures connection quality and network embeddedness, suggesting that strategic positioning within influential investor clusters matters more than connection quantity. This finding indicates VCs should prioritize connections with central network players to enhance deal flow access and investment performance. Network centrality emerges as the strongest predictor of VC success, particularly for unicorn creation, surpassing traditional factors like experience and geography. The California effect confirms startup hubs' persistent importance, while industry focus benefits suggest specialization advantages in high-potential sectors.

Paths to Influence Follow-on investments from influential VCs provide the strongest path to network centrality, outweighing co-investment or providing follow-on funding. This finding emphasizes the importance of validation effects in VC networks, supporting Hsu (2004)'s research on certification by prominent VCs. These results suggest emerging VCs should prioritize early-stage investments capable of attracting follow-on funding from established firms, potentially through smaller initial investments in high-potential companies. Such strategy may accelerate network centrality gains more effectively than direct co-investment attempts.

Dynamic Network Evolution Network analysis reveals distinct temporal patterns in VC investments. Investment burstiness suggests critical periods for network advancement, while memory effects highlight the importance of repeat collaborations, supporting Sorenson and Stuart (2001)'s findings on VC relationship persistence. Non-stationarity across funding stages demonstrates evolving network dynamics throughout company lifecycles. These patterns suggest VCs should adapt network strategies to capitalize on high-activity periods, prioritize sustained co-investor relationships, and adjust approaches across investment stages.

GIV: Granular Instrumental Variables The GIV analysis provides causal evidence of influential VC connections' impact on network position. Endorsement connections yield the strongest effect (15.6% k-shell increase), followed by syndication (11.8%) and backing connections (9.2%), emphasizing timing's importance in network formation. The non-significant anticipatory connection test strengthens causal interpretation, while heterogeneous effects reveal smaller firms gain more from influential connections. This finding suggests a potential counterbalance to the Matthew effect in VC networks.

These results extend social capital theory in professional networks and offer practical implications: firms, especially smaller ones, should prioritize early involvement with influential VCs through strategic co-investments or mentorship. For entrepreneurs, attracting well-connected investors may create cascading network benefits. Future research could examine sector-specific network dynamics and investigate how centrality improvements translate into tangible benefits such as enhanced deal flow.

Triple Difference (DDD) The analysis reveals key insights into VC network influence dynamics. Network validation from prominent VCs, particularly through follow-on investments in peripheral VCs' portfolio companies, proves more impactful than direct networking efforts. This finding emphasizes reputation effects in venture capital, where established players' endorsements significantly drive network position.

The strong relationship between prior network position differences and K-shell value changes indicates "network momentum," suggesting a Matthew effect where well-positioned firms more easily improve their standing. However, GIV analysis shows smaller firms gain larger advantages when they succeed in connecting with influential VCs. Robustness checks strengthen these findings: anticipatory connections show no significant effects, indirect connections reveal similar but smaller patterns, and lead-lag analysis rules out reverse causality. These results confirm that strategic connections with influential VCs causally improve network position.

These findings extend social capital theory in professional networks and suggest practical strategies: VCs should prioritize early involvement in promising startups and focus on attracting influential investors, while entrepreneurs should recognize that well-connected early-stage investors may facilitate future funding access.

8 Conclusion

This study examines venture capital network dynamics through k-shell decomposition and dynamic network analysis. The GIV analysis establishes causal relationships between influential VC connections and network centrality improvements, while Triple Difference analysis reveals that receiving follow-on funding from influential VCs most effectively enhances network position, regardless of investment outcomes. For VC firms, results suggest prioritizing portfolio companies' ability to attract influential investors over targeting investments already made by influential VCs. For entrepreneurs, findings highlight the importance of investors' network positions in early-stage funding decisions. Study limitations include incomplete capture of informal relationships and focus on US-based firms. Several opportunities for future research emerge. Examining sector-specific network dynamics would enhance understanding of industry variation. Investigating network position's impact across startup lifecycle stages could yield practical insights. Analysis of international VC relationships would test finding generalizability. Research on network position effects on deal flow and fund performance would illuminate tangible benefits. Longitudinal studies of network position and firm performance co-evolution could reveal long-term dynamics. This research advances understanding of VC network dynamics while providing practical insights for industry participants and opening new avenues for scholarly investigation.

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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 Endorsement. Conversely, if Investor A invests after Investor B, the Connection Reason is classified as Backing . 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.

9.3 Parallel Trend Assumption

Table 14: Triple Difference Models Results (Non-Significant)

Effect Type	**Coefficient**	**Std. Error**
Main Effects		
Intercept (β_0)	0.0045	(0.0052)
$\text{Placebo}_{C(AB),t}$: backing (β_1)	-0.0123	(0.0145)
$\text{Placebo}_{C(AB),t}$: syndication (β_1)	-0.0089	(0.0137)
$\Delta K\text{s}_{(AB),(t-1)}$ (β_2)	0.0412	(0.0623)
$\text{I}_{B,(t-1)}$ (β_3)	0.0291	(0.0547)
Two-Way Interactions		
$\text{Placebo}_{C(AB),t}$: backing $\times \Delta K\text{s}_{(AB),(t-1)}$ (β_5)	-0.0248	(0.0579)
$\text{Placebo}_{C(AB),t}$: syndication $\times \Delta K\text{s}_{(AB),(t-1)}$ (β_5)	-0.0183	(0.0527)
$\text{Placebo}_{C(AB),t}$: backing $\times$ $\text{I}_{B,(t-1)}$ (β_6)	-0.0136	(0.0458)
$\text{Placebo}_{C(AB),t}$: syndication $\times$ $\text{I}_{B,(t-1)}$ (β_6)	-0.0074	(0.0432)
$\text{I}_{B,(t-1)}$ $\times \Delta K\text{s}_{(AB),(t-1)}$ (β_7)	0.0167	(0.0491)
Three-Way Interactions		
$\text{C}_{(AB),t}$: backing $\times$ $\text{I}_{B,(t-1)}$ $\times \Delta K\text{s}_{(AB),(t-1)}$ (β_{11})	0.0053	(0.0118)
$\text{Placebo}_{C(AB),t}$: syndication $\times$ $\text{I}_{B,(t-1)}$ $\times \Delta K\text{s}_{(AB),(t-1)}$	0.0041	(0.0107)
Controls and Model Fit		
Controls inv A	Yes	
Controls inv B	Yes	
Fixed Effects C	Yes	
Observation Number	3,803,954	
R squared	12.4%	

Note: No coefficients are statistically significant ($p > 0.05$)

A critical assumption underlying the empirical strategy in this paper is that, absent treatment, treated and control venture capital firms would have followed similar trends in their network centrality over time. This is known as the parallel trends assumption, which ensures that any estimated effects from the triple difference (DDD) methodology capture the causal impact of forming connections with influential venture capital firms rather than reflecting pre-existing differences in network evolution between treated and control firms. If this assumption does not hold, the estimated treatment effects could be biased, as firms that eventually form influential connections might have already been on a trajectory of increasing centrality prior to treatment. This would confound the causal interpretation of the results, as any observed post-treatment differences could merely reflect selection dynamics rather than the influence of network formation itself. Establishing the validity of the parallel trends assumption is therefore essential to ensuring that the estimated treatment effects are not driven by unobserved heterogeneity among firms that later receive influential backing.

To empirically assess the validity of this assumption, I conduct a placebo triple difference test that applies the same estimation framework used in the main analysis but assigns a placebo treatment window occurring six to twelve months before the actual connection event. If firms on track to receive influential connections already exhibited systematically different network centrality trajectories prior to the actual treatment, one would expect to observe a statistically significant effect in this placebo specification. The results, presented in Table 14, indicate that the coefficient on the placebo treatment is small in magnitude and statistically indistinguishable from zero, suggesting that firms in the treated group did not exhibit significantly different network dynamics in the months leading up to treatment compared to firms in the control group. Furthermore, interaction terms between the placebo treatment and prior network position also yield statistically insignificant estimates, reinforcing the conclusion that the evolution of network centrality did not systematically differ between treated and control firms prior to the connection event. The relatively low explanatory power of this placebo regression further suggests that the placebo treatment does not meaningfully predict changes in k-shell position.

The findings from this analysis provide strong empirical support for the parallel trends assumption, which is a necessary condition for the validity of the triple difference identification strategy. By demonstrating that firms that later receive influential backing do not exhibit differential network trends prior to treatment, the results confirm that the estimated effects in the main analysis are not driven by selection bias or pre-existing differences between treated and control firms. This validation strengthens the credibility of the causal interpretation, reinforcing the conclusion that forming connections with influential investors plays a meaningful role in shaping network centrality in venture capital markets. The importance of establishing this assumption extends beyond the specific application in this study, as failure to account for parallel trends can lead to erroneous conclusions in difference-in-differences or triple difference settings. By explicitly testing for and confirming the validity of this assumption, this study provides greater confidence in the robustness of its findings and in the broader implications regarding the role of network structure in venture capital investment dynamics.