Financial Performance Analysis Using Co-investment Networks:
Leveraging Bipartite Networks and Their Projections

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Abstract. This study examines the relationship between Venture Capital (VC) positions in co-investment networks and their financial performance, focusing on the "Network Hypothesis." While prior research, such as Li et al. (2024), used simple networks capturing only direct co-investments, this study incorporates bipartite and bipartite projection networks to better reflect indirect investment relationships via portfolio companies.

Using data from 66,220 funding rounds in Japan (2000–2023) and IPO records from SPEEDA, three types of co-investment networks are constructed. Six centrality indicators and four time-series metrics were calculated. Hierarchical clustering (Ward's method) is applied to selected VCs, grouping them into five clusters. Clustering performance is evaluated using IPO rates by company count and investment amount.

Results show that the bipartite network achieved the highest clustering accuracy, particularly when using degree centrality, highlighting the number of companies a VC invested in as a key predictor of performance. This suggests that bipartite structures more effectively capture investment behavior and financial outcomes than simple networks.

In conclusion, the study demonstrates that bipartite networks, especially degree centrality, offer a powerful tool for classifying VCs based solely on co-investment patterns, revealing distinct groups with different investment behaviors and outcomes.

Keywords: Venture Capital, Network Analysis, Co-investment Network.

1 Background

This study analyzes venture capital (VC) investment, which plays a vital role in supporting the growth of unlisted emerging companies by providing financial resources and enhancing corporate value. VCs not only act as funding providers but also contribute to technological innovation and industrial development. It has been reported that a significant proportion of companies that go public (IPO) have received investment from VCs.

In venture investment, co-investment—where multiple institutions or individuals invest jointly—is frequently observed. There are four primary motivations behind co-investment. The first is the risk diversification hypothesis, which posits that co-investment reduces the investment amount per case and helps diversify risk across the overall portfolio. (De Clercp and Dimov (2004)) The second is the knowledge-sharing hypothesis, which emphasizes that sharing information and expertise with other VCs enables more informed investment decisions. (Lerner (2022)) The third is the value-added hypothesis, which posits that collaboration among VCs can provide management support and network resources, ultimately leading to higher investment returns. (Brander et al. (2002)) The fourth is the network hypothesis, which argues that building relationships with other VCs across industries and regions facilitates access to investment information and creates opportunities to participate in high-potential projects. (Sorenson and Stuart (2001))

This research focuses particularly on the network hypothesis and examines co-investment networks, which are formed based on VC investment activities. Previous studies have shown that co-investment networks play a key role in overcoming geographic barriers to VC investment, restricting the entry of external VCs, and facilitating exit opportunities in foreign markets. These networks have also been used to identify regional hubs within the VC market, analyze relationships with foreign countries, and examine the transmission of information within the domestic market. Moreover, the literature indicates a strong relationship between a VC's position (influence) within the network and its investment performance. Enhancing one's influence within such a network is, therefore, considered a strategically important objective for many VCs.

2 Objectives

While prior studies have empirically demonstrated the relationship between network-based positional indicators and VC financial performance, their analyses were primarily based on "simple networks," which captured only direct co-investment relationships among VCs within the same funding round. These networks failed to reflect the broader relational structure among VCs who invested in the same startups at different times or through different mechanisms. This limitation can be addressed by employing "bipartite networks" and their "projected networks," which allow for the identification of relationships among VCs based on shared investment experience in the same companies, regardless of the funding round.

In this context, our study aims to achieve the following: first, to examine whether the information captured by bipartite and bipartite projection networks contributes to improving clustering accuracy when grouping VCs based on financial performance; second, to identify effective indicators for predicting VC financial performance; and third, to offer insights into the structure of co-investment networks among VCs investing in Japanese startups.

3 Method

This study uses data from "SPEEDA Startup Information Research," operated by Uzabase Inc. Three datasets were utilized: first, funding round data on 66,220 investments conducted between January 2000 and December 2023; second, data on all investment institutions registered in the SPEEDA database; and third, IPO data on companies that went public between August 2000 and October 2024.

Following the methodology employed by previous research, the analysis proceeded in several steps. First, three types of co-investment networks were constructed using the funding data: simple networks connecting VCs that co-invested in the same funding round, bipartite networks connecting VCs and startups, and bipartite projection networks connecting VCs with shared investment experience in the same companies. These were designed as cumulative networks (following Li et al. (2024)) to capture the temporal evolution of co-investment behavior from 2000 to 2023.

Second, six types of centrality measures were computed for each network to evaluate the influence of individual VCs: degree centrality, closeness centrality, betweenness centrality, eigenvector centrality, harmonic centrality, and k-shell values. However, eigenvector centrality, harmonic centrality, and k-shell values were not calculated for bipartite networks due to interpretational constraints.

Third, to capture the temporal dynamics of the centrality indicators, four features were extracted: the length of the time series, the 2023 value of each indicator, the difference between the entry-year and 2023 values, and the area under the curve of a line fitted to the time series.

Fourth, the target VCs for clustering were filtered to include only entities classified as "VCs" or "foreign VCs." Institutions in the bottom 10% in terms of total investment amount were excluded from the analysis. In addition, only VCs that had at least one investee company go public were retained, and minimum thresholds for the number of unique investee companies (ranging from 2 to 10) were applied.

Fifth, the selected VCs were clustered into five groups using Ward's hierarchical clustering method, based on the extracted centrality features. The clustering results were then evaluated using a two-dimensional plot of financial indicators—IPO rate by company counts and IPO rate by investment amount—and cluster performance was assessed by measuring intra-cluster and inter-cluster distances.

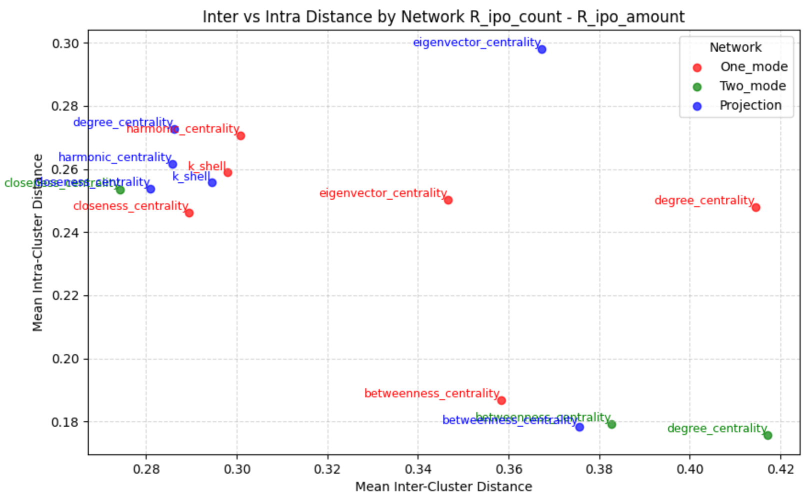

Figure 1. Clustering results

4 Results and Discussion

Figure 1 illustrates clustering accuracy under the condition that the number of unique portfolio companies is six or more. The X-axis represents intra-cluster distance (where lower is better), and the Y-axis represents inter-cluster distance (where higher is better). Indicators that appear closer to the bottom right corner of the plot are interpreted as yielding higher clustering accuracy.

Among the three network types, bipartite networks consistently produced the most accurate clustering results, followed by simple and bipartite projection networks, which exhibited similar levels of performance. These results suggest that the structural properties of bipartite networks—specifically their ability to capture broad investment behaviors regardless of funding round or investment type—are especially effective for distinguishing between VCs based on financial performance.

Regarding individual centrality indicators, degree centrality in bipartite networks demonstrated the highest clustering accuracy. This suggests that the number of unique investee companies, as captured by degree centrality in bipartite networks, is a more reliable predictor of VC performance than metrics related to co-investment frequency or connections with other investors. Betweenness centrality followed closely in accuracy, implying a possible relationship between acting as an information broker and achieving higher financial performance.

The optimal indicator, in terms of clustering accuracy, was bipartite network degree centrality when the minimum number of unique investee companies was set to six.

Using this indicator, VCs were clustered into five distinct groups with differing investment behaviors and financial performance outcomes. Cluster 1 included VCs with the longest activity periods and strongest recent influence, often investing in trending IT sectors. Their IPO rate was moderate, and their influence peaked around 2000–2003. Cluster 2 comprised VCs with long activity histories but declining influence, characterized by the highest IPO rates and diversified investments. This may reflect the maturity of their portfolios and successful exits. Cluster 3 represented newly active VCs with short activity spans and a strong focus on R&D-oriented ventures, characterized by the low IPO rates likely due to insufficient time for exits and the long commercialization timelines typical of such companies. Cluster 4 included VCs with long activity periods but low recent influence, showing no particular characteristics, which may indicate the limits of the chosen features and the need for further analysis. Cluster 5 comprised VCs with rapidly growing influence in recent years, focusing less on R&D ventures and showing relatively low IPO rates, possibly due to short activity periods. The presence of VCs with influence peaks around 2008 suggests potential value in incorporating maximum historical centrality values in future models.

5 Conclusion

This study constructed three types of co-investment networks based on investment records from 2000 to 2023 and used time-series features of centrality measures to cluster VCs. The results confirmed that bipartite networks outperformed both simple and projection networks in accurately clustering VCs based on their financial performance. In particular, clustering based on degree centrality in bipartite networks proved highly effective for identifying meaningful differences in VC behavior and outcomes.

Several challenges remain for future research. First, while specific centrality indicators—especially degree and betweenness—yielded accurate clustering results, their precise relationships with financial performance were not fully explored. Further statistical modeling, such as multiple regression analysis, is necessary to clarify these associations. Second, the current network construction did not capture the frequency of investment. Revising the network structure to incorporate such information could better reflect the strength of VC–VC and VC–startup relationships. Third, while this study used IPO rates as performance indicators, it was not possible to assess actual returns at the time of IPO due to data limitations. Future work should explore the possibility of estimating VC revenues and including mergers and acquisitions (M&A) as alternative exit outcomes. Fourth, the clustering analysis does not control for macro-economic or sector-specific confounders, which may bias the interpretation of results. Accounting for these external factors could strengthen the robustness of the findings. Finally, while this study considered co-investment networks in a static framework, incorporating dynamic network evolution together with realized investment returns would provide a more comprehensive understanding of VC performance and further deepen the contribution.

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