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Who Are the Elites in the Venture Capital Industry?—Investigation of Elite-Club Boundary in a Co-Investment Network

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Abstract: Existing research suggests that elite clubs exist in venture capital markets, but a standard for determining their size and composition is lacking. This paper addresses this challenge by using the weighted k-means sorting algorithm to construct a research framework for elite clubs. Validating the framework with investment events data from China's venture capital market (2001–2018), intriguing findings emerge. The ranking of Venture Capitalists (VCs) follows a power-law distribution, providing evidence for elite clubs' existence. The analysis identifies a turning point in the score curve, serving as a valuable indicator for club boundaries. Elite clubs demonstrate relatively high stability, maintaining advantages and elite status in future competitions. Empirical validation confirms the proposed framework's superior stability compared to existing methods. Importantly, elite club members outperform non-elites significantly. This paper effectively identifies elite clubs in the Chinese venture capital market, helping other VCs recognize potential partners, access high-quality information, and enhance investment performance.

Key words: venture capital; co-investment network; elite club; boundary; ranking

1 Introduction

In the Chinese venture capital market, there are main actors (hereafter known as "elites") that lead a group of smaller companies (hereafter known as "followers") to make an investment, which constitute a unique center-satellites investment structure[1]. Major actors play a leading role in various aspects of the investment process. They actively search for investment opportunities, identify investment objectives, develop comprehensive investment plans, and carefully select and evaluate potential partners. For these reasons, we call them "elites"[2]. These elite actors not only serve as lead investors in investment events but also engage in collaborative efforts to establish connections among different center-satellite groups. They act as bridges, facilitating the flow of diverse resources and information between these groups. This collaborative approach allows for the efficient exchange of valuable assets and knowledge within the venture capital ecosystem. In other words, the VC network is a special type of small-world[3]. As the elites collaborate frequently with each other, the elite-network emerges, and the elite-club develops into the Venture Capital (VC) network's center[2, 4, 5].

In the realm of VC, elite clubs comprise VCs with high status, indicating their central position relative to other actors in the VC network[6, 7]. Status advantages help them reduce alter-centric uncertainty and the liability of foreignness[8], increase the legitimacy and desirability as a partner[9, 10], improve their access to local resources[11], promote innovation[12], receive unsolicited help[13], and improve investment performance[14]. The theory of social embeddedness and preferential attachment further explains that VCs are inclined to collaborate with high-ranking elites, as they prefer to build relations with central nodes in a

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network[15, 16]. The frequent collaboration among high-status members of elite clubs fosters the exchange of valuable resources and information channels, exploiting the Matthew effect—where the already influential actors become even more potent. Furthermore, when other VCs co-invest with high-status elites, they can tap into their wealth of high-quality investment information, management skills, and experience, thereby enhancing the value of investment projects and ultimately improving investment returns[17]. Moreover, the reputation effect of elites serves as a strong authentication and transaction guarantee for entrepreneurial enterprises, which in turn helps startups gain a significant competitive advantage over their industry competitors[18–20]. In the long run, collaborating with elites can bring more opportunities and prestige for other VCs. Establishing a stable cooperative relationship with elites not only provides access to valuable resources but also becomes a valuable social resource[21]. These reasons drive non-elites to actively seek identification and collaboration with elites in the venture capital ecosystem.

Identifying elites is undeniably crucial, yet it poses several challenges. Many studies have employed diverse methods to identify elites or leadership groups. Kadushin[22] proposed the relational approach using social network analysis to find a central circle of policymakers within the elite. Knoke[23] summarized four distinct strategies: the positional, the decisional, the reputational, and the relational. Larsen and Ellersgaard[24] used a modified version of k-cores developed by Seidman[25]. Some other methods include ranking degree centrality[26, 27], eigenvector centrality[28], betweenness centrality[26, 27], closeness centrality[29], k-core[30], PageRank[28], the number of members[24], and Delphi method[31]. Defining network boundaries is a crucial foundation for studying the social structure of elite networks. However, traditional methods often lack clear criteria for determining the size or composition of the elite club, leading to variations in measurement criteria and reliance on numerous ad hoc decisions. Questions such as whether the elite club should consist of a small circle of 30 individuals or a larger group of 300 still need to be addressed[24].

In this paper, we tackle the challenges of inconsistent identification for different indicators and reliance on temporary decision-making by proposing a novel research framework for identifying elite clubs based on the weighted k-means sorting algorithm. This framework effectively addresses the problem of determining the boundaries of elite clubs. Applying this new approach to the Chinese venture capital market, we discover some interesting findings. The ranking of VCs follows a power-law distribution, and there is a distinct turning point in the score curve, allowing us to identify elite clubs by drawing cumulative score distribution curves. These elite club members exhibit a high retention rate, and they strategically set boundaries to limit the inclusion of too many VCs as core members, thereby avoiding excessive resource distribution. Empirical validation demonstrates that this new identification framework is more stable than other methods, and the performance of elite club members is significantly higher than that of non-elites.

The rest of this paper is organized as follows. Section 2 reviews the literature on elites and high status, an elite club and its formation, and related methods for identifying elites. Section 3 develops the research framework including data, network definition, indicators construction, ranking, fitting, and identifying. Section 4 presents elite clubs identification and changes in elite clubs. Section 5 shows elite clubs investment performance. Section 6 concludes the paper with a discussion on information management.

2 Literature Review

2.1 Elites and high status

Elites, as defined by the Oxford dictionary, are a group of people in a society who hold significant power and wield considerable influence. In the context of investments, a similar phenomenon is observed in China's venture capital industry, where there is typically a leading VC responsible for spearheading investment activities. This VC takes charge of searching for promising investment opportunities, initiating investment projects, and evaluating and selecting partners. In this setup, the VC assumes a leading role in the investment process, while the selected partners are primarily required to follow along with the VC's decisions. In other words, these leading VCs form a center-satellites group, which we refer to as "elites"[1]. Elites typically occupy a central position within their local circles, and this centrality can be measured by their social status. The concept of status, originally proposed by Weber, refers to an effective claim to social esteem in terms of positive or negative privileges[32]. Elites typically occupy a central position within their local circles, and this centrality can be measured by their social status. An actor's status is significantly influenced by their affiliations and dependencies[7] and it is formally defined as the actor's centrality relative to others within the entire industry network[6, 33]. Therefore, elites in the venture capital industry often hold high social status.

In the venture capital market, where uncertainty about the quality and credibility of potential trading partners is common, status plays a crucial role as a signal of quality[34]. Elites with high status leverage their information and social connections to access more social resources and secure high-quality investment opportunities. Furthermore, the projects they invest in have a higher likelihood of attracting follow-up investments from other venture capital companies, providing clear financial advantages[35]. Moreover, status is closely linked to investment performance, as evident in various studies. For example, the status of VCs exhibits a significant positive correlation with their success in exiting investments[36]. The status of VCs also has a considerable positive impact on the scale of their fund-raising efforts[19]. Evidence from the US[35] and Europe[37] shows that the VC firm located close to the center of the network performs better. High-status VCs can provide better value-added services for enterprises[14] and have a more complete relationship network, meaning that they can better play the role of information intermediary[38].

2.2 Elites and their co-investment

Co-investment is a prevalent practice in the venture capital industry. However, the network actors in this industry are not equal due to the influence of specific cultural and social backgrounds. As a result, there are qualitative differences in social identity, resource access, social responsibility[22], and behavior between actors positioned at the center of the network and those at the edge of the network. This unequal distribution of status and resources can significantly impact the dynamics and outcomes of co-investment activities within the venture capital ecosystem. In this context, collaborating with high-status VCs represents a distinctive joint strategy within the Chinese venture capital market. Drawing on rational choice theory, the financial perspective, and resource-based theory, the primary motives for co-investment can be categorized into three key points: (1) Obtain diversified and heterogeneous resources[39]. (2) Diversify investment and disperse risks[40, 41]. (3) Synergism. The implementation of diversified decision-making plans enables the venture capital firms to harness synergies and gain competitive advantages. By collaborating, lower-status VCs often seek the favor of high-status elites to gain network advantages[42]. The high-status VCs hold a prominent position in the venture capital network, possessing extensive connections and influence within the industry. Collaborating with these elite VCs not only enhances the visibility and reputation of the lower-status VCs but also provides them with access to valuable opportunities and resources. The network advantages of high-status VCs enable the lower-status VCs to expand their reach and strengthen their position within the venture capital ecosystem. From the resource-based theory perspective, the purpose of co-investment between other VCs and elites is to enhance the value of investment projects and maximize returns by leveraging the investment resources offered by these elite VCs. These resources include high-quality investment information, advanced management technology, and extensive investment experience possessed by the elites. In addition, the status effect of collaborating with elite VCs provides startups with assurance and certification during transactions[18–20], granting them a greater competitive advantage over their competitors. Furthermore, enterprises supported by high-status VCs often demonstrate better market performance, benefiting from the strategic value of such partnerships.

Views based on rational choice often result in individual behavior that is limited by short-term thinking and self-interest (individual myopia). To overcome the constraints of individual rationality, network actors in the venture capital industry do not solely focus on maximizing their immediate gains in each transaction. Instead, they actively cultivate a favorable network environment, emphasizing long-term development and relying on the robustness of their networks and trust in "rational collective decision-making processes” rather than solely pursuing immediate economic returns. As a result, their strategies are often oriented towards navigating the uncertainties of the unknown environment, rather than relying solely on familiar factors. Long-term thinking and strategic planning are prevalent, leading network actors to prioritize relationship-building over immediate economic gains. Collaborating with high-status elites is seen as a means to establish enduring and mutually beneficial partnerships. As institutional uncertainty and information asymmetry characterize long-term business relationships, the logic behind resource-driven decision-making gradually shifts towards relationship-driven approaches. To complement the rational choice view, the perspective of social embeddedness theory is introduced, recognizing the importance of social connections and interdependence in shaping network actors’ behavior[1], this perspective emphasizes the role of relationships, trust, and collective decision-making in mitigating individual myopia and driving long-term success within the venture capital industry.

As mentioned in the interview, elites in the venture capital industry possess a strong reputation and an impressive investment portfolio, which contributes to their status and influence. Smaller venture capital companies aim to leverage the reputation of elites by making monetary investments, as such collaborations directly enhance their own reputation. Moreover, small VCs may strategically navigate relationships within the elite circle, gradually moving towards the inner circle. This gradual progress can eventually lead the small VC to become an elite itself, establishing its own influential network of relationships[1]. Preferential attachment theory suggests that actors in a network tend to prefer building connections with central nodes. By collaborating with elites, small venture capital firms or circle members not only gain access to valuable investment information but also establish more meaningful connections with other companies in the elite network. This is particularly advantageous as these elite companies often engage in collaborations with other prominent players in the industry[1]. By strategically aligning with elites, smaller VCs can access valuable resources and opportunities that contribute to their growth and success in the competitive venture capital landscape. Based on social embeddedness and preferential attachment theory, in the long run, long-term cooperation with elites can bring more opportunities and a better reputation. Stable cooperation with elites provides not only a channel for resources, but also a social resource.

2.3 Elite club and its formation

As the central figures within their small circles, elites take the lead in investment decisions, gradually forming partnerships with followers. While stable relationships and effective communication are fostered within these circles[43], there is a potential for “interlocking” among members due to increasing homogeneity[44]. In other words, staying within the same circle for too long may lead to inefficiencies[14], particularly for elites in center-satellite groups. Therefore, elites proactively seek cooperation outside their circles. According to the concept of structural embeddedness, elites also seek partners outside of their circles to gain access to heterogeneous resources and channels, and VCs with more mutual relations are more likely to be selected as partners[5, 45]. Generally speaking, elites engage in more cooperation and networking within the network than non-elites, resulting in more mutual relationships with other elites and increased opportunities to become direct partners. Over time, frequent collaborations among elites establish increasingly close relationships between both parties, leading to the emergence of an elite clique at the center of the entire network. This phenomenon highlights the significance of cooperation outside their initial circles, as it strengthens the overall interconnectedness and influence of elite actors within the venture capital industry.

Some theoretical studies have attempted to elucidate the formation of the elite clique. According to elite theory, companies are driven to protect their status by collaborating with other companies of equal status[46]. Hence, elites are more inclined to unite with other elites who share similar status. Social network theory supports the notion that homogeneous groups tend to have closer relationships, suggesting that enterprises with equal status are more likely to form alliances[47–49]. Furthermore, network theory posits that a clear core-periphery structure tends to develop between the influential and the influenced[50], leading elites to establish strong ties among themselves. The elite clique offers several advantages. Stevenson and

Radin[51] believed that the social capital derived from close relationships between elites is a potent factor in gaining greater influence, exhibiting the Matthew effect, whereby the influential become even stronger. In the elite clique, a VC can cultivate more diversified and high-quality relationships, with the idea that one person's behavior impacts the entire company. This interconnectedness within the elite clique enhances decision-making power and access to valuable resources, contributing to the collective strength and prominence of the elites in the venture capital industry.

2.4 Identifying an elite club

Cooperating with elites has been shown to positively impact performance, and becoming a part of elite clubs can significantly increase decision-making influence. As a result, accurately identifying elites and elite clubs becomes a top priority for VCs to enhance their overall influence. Elites typically occupy central positions within the network and hold high social status. The process of identifying elites is essentially equivalent to determining their social status, which can be achieved through various ranking methods.

2.4.1 Single indicator

The most common method of identifying status is using centrality measures, such as degree centrality[52], closeness centrality[53], betweenness centrality[54], eigenvector centrality[55], *k*-core[30], and PageRank[56]. Other centrality indicators are also used to measure status, such as UW-PageRank, IPRA, HillTop, TrustRank, LeaderRank, and CiteRank. Some studies also use various frequency domain indicators to measure status, such as company scale, experience, and investment frequency. Measures and research are shown in Table 1.

Each indicator used to measure status and centrality in the venture capital network provides distinct insights

Table 1 Single indicators.

Indicator		Measure	Reference
Centrality indicator	Degree centrality	Number of edges directly connected to the node	Fu et al.[52]; Gao et al.[53]
	Closeness centrality	How close a node is to other nodes	Sabidussi[29]; Fu et al.[52]; Gao et al.[53]
	Betweenness centrality	Number of shortest paths through a node	Freeman[54]
	Eigenvector centrality	Importance of neighbor nodes connected to this node	Bonacich[55]
	k-core	Subgraph that conforms to the specified *k* kernel degree	Kitsak et al.[30]; Perc[57]
	PageRank	Importance of a roughly estimated website by calculating the number and quality of web links	Richardson and Domingos[56]; Page et al.[58]
	TrustRank	A ranking algorithm based on link relation	Gyöngyi et al.[59]
	UW-PageRank	When extracting keywords, disambiguation is eliminated and the most important meaning is selected (improvement of PageRank)	Wang et al.[60]
	LeaderRank	When ranking, a background node is added for bidirectional connection with all nodes (improvement of PageRank)	Lyu et al.[61]; Li et al.[62]; Bian and Deng[63]
	CiteRank	A multi-dimensional hybrid ranking method (improvement of PageRank)	Jomsri et al.[64]
	IPRA	A method based on resource allocation (IPRA) to identify influential nodes (improvement of PageRank)	Zhong and Lyu[65]
	HillTop	A method for ranking search engine results by the number and quality of web pages linked	Bharat and Mihaila[66]
Frequency domain indicator	Scale	Number of firms a VC has invested in	Bygrave[67]; Cable and Shane[68]; Walske et al.[69]
		Number of industries a VC has invested in	Yang et al.[70]
		Number of rounds a VC has invested in	Yang et al.[70]
		Number of countries a VC has invested in	Yang et al.[70]
		Number of provinces a VC has invested in	Yang et al.[70]
		Number of seed stages a VC has invested in	Yang et al.[70]
		Number of initial stages a VC has invested in	Yang et al.[70]
		Number of expansion stages a VC has invested in	Yang et al.[70]
	Experience	Investment experience of VC	Cumming and Dai[71]

into the influence and positioning of nodes (e.g., VCs) within the network. Degree centrality captures the overall connectedness of a node to other nodes, representing its potential to access and disseminate information and resources. Betweenness centrality identifies nodes that act as bridges or intermediaries in the network, facilitating the flow of information and transactions between other nodes. Eigenvector centrality emphasizes the importance of connections to other highly connected nodes, indicating a node's potential to access valuable resources through its associations. Frequency domain indicators focus on node-specific attributes and investment behavior patterns. Different centrality measures have distinct meanings, calculation methods, and outcomes, making it a challenging task to choose the most appropriate measure to identify influential nodes.

2.4.2 Multiple indicator

The Delphi method is an iterative and systematic approach used to gather and synthesize expert opinions to reach a consensus on a specific topic. In this case, the Delphi method is employed to identify elites in the venture capital industry. The process begins by presenting the experts with a clear definition of elites in the context of the venture capital market. Next, the experts are asked to provide their opinions and insights regarding which venture capital firms they consider as elites. The collected opinions are then compiled and presented back to the experts without revealing their identities. The process is iterative, and additional rounds of feedback are sought from the experts until a consensus is reached and the opinions become consistent. Ultimately, after several rounds of the Delphi method, a final list of 42 elites is obtained.

Multiple Criteria Decision Analysis (MCDA) is a systematic approach used to evaluate and rank alternatives based on multiple criteria or objectives. It is a decision-making tool that helps in handling complex and multidimensional problems, where there are several conflicting criteria that need to be considered simultaneously[72]. In MCDA, decision-makers identify a set of criteria that are relevant to the problem at hand and assign weights to each criterion based on its relative importance. Then, alternative solutions or options are assessed against these criteria to determine their performance or suitability. The evaluation can be done using various quantitative or qualitative methods, such as numerical scoring, pairwise comparisons, or linguistic assessments.

The Analytic Hierarchy Process (AHP) is a decision-making methodology that allows individuals to systematically and quantitatively evaluate complex problems with multiple criteria[73]. It involves structuring the problem into a hierarchical model, determining pairwise comparisons to establish relative importance, and computing priority weights to facilitate informed decision-making. AHP is widely used in various fields, such as business, engineering, and social sciences, to prioritize options and make well-balanced choices.

Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is a widely used comprehensive evaluation method that effectively captures differences between evaluation objects. Du et al.[74] applied Degree Centrality (DC), Closeness Centrality (CC), and Betweenness Centrality (BC) in TOPSIS to generate ranks for evaluating a node's influence. The fundamental principle of the TOPSIS method involves ranking evaluation objects based on their distances from the most optimal and least optimal solutions. The object closest to the optimal solution while farthest from the least optimal solution is considered the best solution, while others are deemed suboptimal.

Using multiple indicators for ranking allows for a more comprehensive and holistic measurement, considering the unique characteristics of each indicator. However, this approach is primarily aimed at achieving a comprehensive ranking and does not provide a clear standard for defining the scope and boundary of the elite. The determination of elites seems to rely more on subjective and temporary decisions, as exemplified by the arbitrary selection of the top 42 as elites. As a result, the method may lack precision and consistency in identifying and classifying elites in the venture capital industry.

2.5 Motivation

Clarifying the boundaries of elite clubs and accurately identifying high-ranking elites are crucial for venture capital firms to find suitable investment partners and enhance their investment performance. However, the current research faces some shortcomings. Using single indicators to rank VCs can lead to inconsistent and inconclusive results due to the varied measurement content and focus of each indicator. The choice of the most suitable indicator remains uncertain, and a clear standard for delineating the boundaries of elites is lacking. Although some comprehensive methods have been introduced to address the limitations of single indicators, the determination of elites still seems to heavily rely on subjective and temporary decisions. As a result, the lack of a standardized approach may hinder the precision and reliability in identifying and classifying elites in the venture capital industry. Further research is needed to develop more robust and objective methods for identifying and defining elites in this context.

3 Research Design

In order to address the limitations of previous research, this article adopts a comprehensive approach by integrating various single indicators proposed in the existing literature and constructs a new research framework for elite clubs, as illustrated in Fig. 1.

3.1 Data collection

The data for this paper were collected from Zero2IPO, and the co-investment network is based on co-investment events from 2001 to 2018. To ensure data consistency, 17 229 items with missing information were removed, resulting in 26 724 co-investment events involving 3715 VCs. Recognizing that the status of VCs can change over time, this paper calculates the VCs' annual centrality and constructs an annual co-investment network. The specific number of nodes and edges in the co-investment network can be found in Table 2.

As can be seen from Table 2, the co-investment network demonstrates a pattern of gradual expansion over time. The number of nodes in the network, representing the VCs participating in joint investments, exhibits a similar upward trend, mirroring the overall growth of the network. The continuous influx of new VCs into the venture capital industry each year indicates a dynamic and competitive landscape. This competition in the venture capital market underscores the significance of thorough analysis of market information. It also highlights the importance of optimizing co-investment behavioral decision-making.

3.2 Defining the co-investment network

The co-investment behavior among VCs is primarily characterized and represented by the co-investment network. In this network, each VC is considered a node, and the connections or edges between nodes are established based on whether there is co-investment behavior between the VCs. The strength of the co-investment relationship is often indicated by the weight of the edges in the network. Various factors can be used to determine this weight, including: number of co-investments, network distance between VCs, circle relationships, and so on.

Defining the co-investment network G, G is an undirected graph and contains ordered triple $(V(G), E(G), \phi_G)$, $V(G)$ is a non-empty node set, $V(G)=\{v_i | i\in(1, 2, \dots, n)\}$, and v_i represents the venture capital in the network. $E(G)$ is the set of edges that are disjointed from the nodes set as $V(G)$ and $E(G)=\{e_{uv} | u, v\in V\}$, and e_{uv} depicts the co-investment relationship between VCs. ϕ_G is the copula function, which defines the relationship between each edge in the network. It characterizes the dependence structure between venture capitalists based on their co-investment behavior. Suppose that there are N venture capital institutions participating in the investment market, and they are collectively investing in K enterprises. Co-investment behavior is defined as two or more venture capital institutions investing in the same enterprise during the same time period $(t, t+\Delta t)$. $A^{\Delta t}=\left\{a_i^{\Delta t} | i\in(1, 2, \dots, n)\right\}$ represents the set of co-investment behaviors of venture capital institutions within the time interval $(t, t+\Delta t)$.

In this set, $a_i^{\Delta t}$ represents the co-investment behavior of the venture capital i with other venture capital institutions during the specified time period. Each element $a_i^{\Delta t}$ can be represented as a binary vector: $a_i^{\Delta t}=(a_{i1}^{\Delta t}, a_{i2}^{\Delta t}, \dots, a_{iK}^{\Delta t})$. If venture capital institution "I" invests in enterprise "q" during the time interval $(t, t+\Delta t)$, then $a_i^{\Delta t}$ will be 1 for that specific enterprise ($a_i^{\Delta t}=1$), otherwise, $a_i^{\Delta t}=0$.

Defining correlation function ϕ_G. The correlation function ϕ_G is defined as follows: $e_{uv}=\phi_G(a_u^{\Delta t}, a_v^{\Delta t})$, where e_{uv} represents the co-investment relationship between venture capital institutions "u" and "v" within a specific time interval $(t, t+\Delta t)$. To calculate e_{uv}, the correlation function ϕ_G employs a sign function

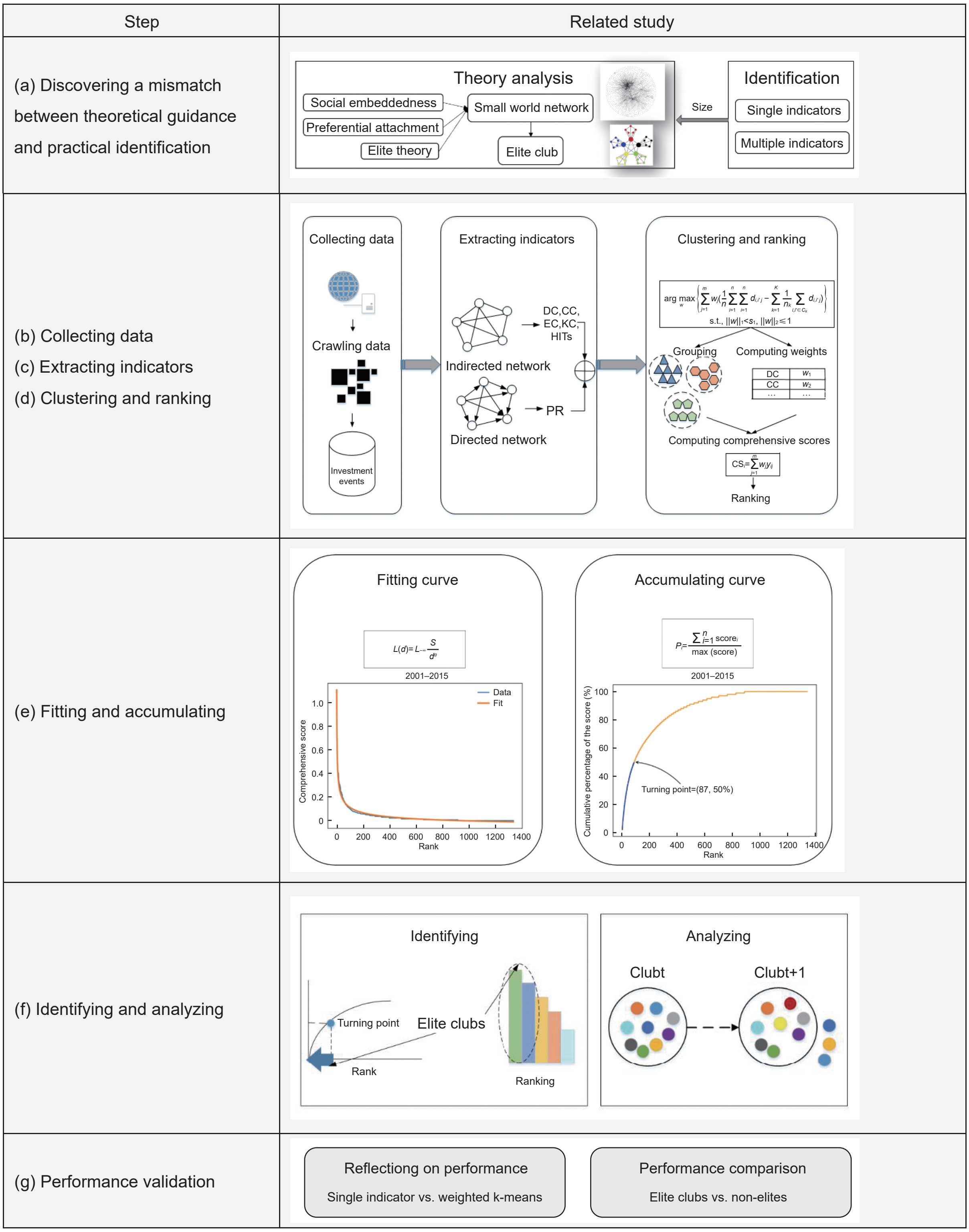


Fig. 1 Research framework. The entire study consists of seven steps: Discovering a mismatch, collecting data, extracting indicators, clustering and ranking, fitting and accumulating, identifying and analyzing, and performance validation.

denoted as $I(a_{uj}^{\Delta t}, a_{vj}^{\Delta t})$, which measures the similarity of co-investment behavior between "u" and "v" in each of the K enterprises within the time interval $(t, t+\Delta t)$. Specifically, if venture capital institutions "u" and "v" both invest in the same enterprise "j" during the same year, then $I\left(a_{uj}^{\Delta t}, a_{vj}^{\Delta t}\right)$ is set to 1, indicating co-

Table 2 Size of co-investment network for 2003–2015.

Year	Number of nodes	Number of edges
2003	72	139
2004	104	203
2005	130	290
2006	187	444
2007	250	644
2008	326	806
2009	407	1001
2010	539	1305
2011	713	1733
2012	826	2026
2013	881	2181
2014	1064	2912
2015	1338	3882

investment similarity, otherwise, $I\left(a_{uj}^{\Delta t}, a_{vj}^{\Delta t}\right)=0$. Using this definition, the co-investment relationship between venture capital institutions "u" and "v" can be computed as $e_{uv}=\phi_G\left(a_u^{\Delta t}, a_v^{\Delta t}\right)=\sum_{j=1}^{K} I\left(a_{uj}^{\Delta t}, a_{vj}^{\Delta t}\right)$, where the summation is performed over all enterprises "j" (from 1 to K) in the time interval $(t, t+\Delta t)$. Applying this correlation function allows the construction of a network of investment relations between venture capital institutions at time $(t, t+\Delta t)$, denoted by $G(t, t+\Delta t)$ or simply G_t. If the observation time is divided into T units, T co-investment networks can be created, denoted as $G_1, G_2, \ldots, G_T$. Each co-investment network captures the co-investment situations over specific periods of time.

3.3 Constructing indicator

In this paper, the co-investment networks G_1, $G_2, \ldots$, G_T are analyzed using various single metrics, including degree centrality, closeness centrality, eigenvector centrality, k-core, and hub scores. These metrics are employed to assess the status of venture capital in different joint investment networks.

(1) Degree Centrality (DC). Degree centrality measures the number of connections a node has in the network. It is defined as $\mathrm{DC}(i)=\sum_{j=1}^{g} x_{ij}(i \neq j)$, where $\mathrm{DC}(i)$ represents the degree centrality of node i, and $\sum_{j=1}^{g} x_{ij}(i \neq j)$ calculates the number of direct connections between node i and other $g-1$ nodes (excluding the connection between i and itself).

(2) Closeness Centrality (CC). Closeness centrality measures the average shortest path length from one node to all other nodes. It is defined as $\mathrm{CC}(i)=\dfrac{n-1}{\sum_{j \neq i} d_{ij}}$, where $\mathrm{CC}(i)$ represents the closeness centrality of node i, and d_{ij} represents the shortest distance from node i to node j.

(3) Eigenvector Centrality (EC). The node's importance depends on both its neighbors' importance and the number of its neighbors. The importance measure of node i is denoted as x_i. The equation for EC is: $\mathrm{EC}(i)=x_i=c\sum_{j=1}^{n} a_{ij}x_j$, where x_j is the importance measure of node i's neighboring nodes, and c is a constant of proportionality.

(4) *k*-core Centrality (KC). k-core identifies closely connected node groups in the network. It represents the largest node group where all nodes have at least k connections within the group. A higher core value indicates that a venture capital institution is closer to the core of the co-investment network, reflecting its greater importance.

(5) Hub Scores (HITs). Hub scores use the HITs algorithm, similar to Web page scoring, to calculate node centrality. When users input keywords, the algorithm provides hub scores and authority scores for matching pages. Hub value represents the sum of authoritative values of all outgoing links, while authoritative value is the sum of hubs on pages where all incoming links are located.

(6) PageRank. The PageRank algorithm defines a random walk model on a digraph using a first-order Markov chain, simulating the behavior of random walkers visiting each node in the digraph. PageRank is recursively defined and calculated through an iterative algorithm.

3.4 Ranking-based weighted k-means

To address the limitations of using a single centrality indicator in characterizing the status of venture capital institutions in the co-investment network, this study employs a weighted k-means clustering algorithm and the TOPSIS method. By synthesizing multiple network centrality indicators, the comprehensive score of each venture capital institution is calculated, and subsequently, they are ranked accordingly.

The weighted k-means algorithm assigns weights to each network centrality index based on their importance. More discriminative indicators receive higher weights, while less discriminative ones may have smaller or even zero weights. The weights are denoted as w_j, and the distance between samples and feature j is represented as d_{ij}. The estimation of weights using the weighted k-means clustering algorithm is achieved through the following equation:

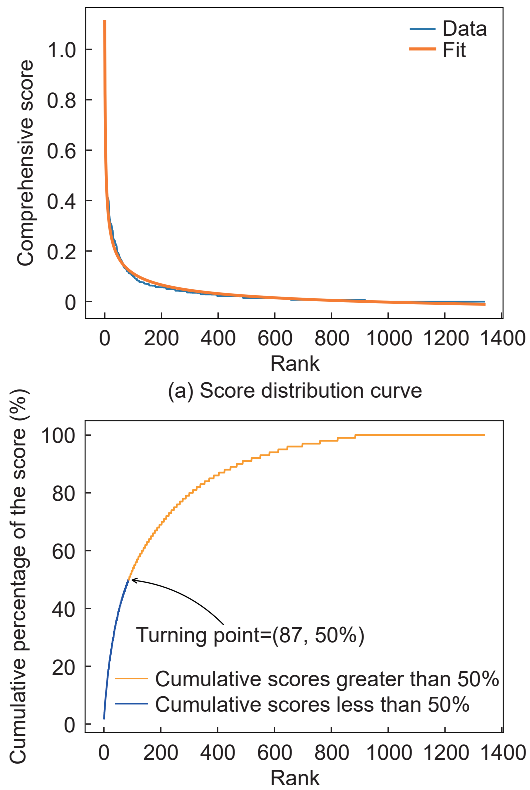
$$\arg\max_{w}\left\{\sum_{j=1}^{m} w_j\left(\frac{1}{n}\sum_{i=1}^{n}\sum_{i=1}^{n} d_{i,i'j}-\sum_{k=1}^{K}\frac{1}{n_k}\sum_{i,i'\in C_k} d_{i,i'j}\right)\right\} \quad (1)$$

$$\text{s.t.}, \|w\|_1 < s_1, \|w\|_2 \leqslant 1$$

where $\|w\|_1=\sum_{j=1}^{m}\left|w_j\right|<s_1$ and $\|w\|_2=\left(\sum_{j=1}^{m} w_j^2\right)^{\frac{1}{2}} \leqslant 1$ are the one norm and two norm penalty functions of the constraint weight size, respectively, $\frac{1}{n}\sum_{i=1}^{n}\sum_{i=1}^{n} d_{i,i'j}$ is the mean value of the square sum of all samples of feature j, and $\sum_{k=1}^{K}\frac{1}{n_k}\sum_{i,i'\in C_k} d_{i,i'j}$ is the square sum of samples within the class in feature j. The weighted k-means algorithm assigns higher weights to feature j if it exhibits significant differences among different clusters, indicating its strong ability to distinguish clusters. Conversely, smaller weights are given to feature j if the differences between different clusters based on this feature are minimal. After completing the weight estimation, the TOPSIS method is employed to calculate the comprehensive score for each investment institution. Based on this score, the ranking of venture capital institutions, representing their status, can be determined.

3.5 Fitting and identifying

Using the weighted k-means method, each VC's score can be determined. By sorting the VC score values in descending order and assigning ranks accordingly (the highest score as 1, the second-highest as 2, and so on), we can plot the VC score distribution diagram. The diagram displays the rank of the VC on the horizontal axis and its corresponding score on the vertical axis, shown as the red curve in Fig. 2a. To analyze the distribution characteristics of VC scores, we apply the curve fitting method proposed by Gu et al.[75] for curve fitting. We assume that the original curve distribution



(b) Cumulative score distribution curve

Fig. 2 Score distribution curve and cumulative score distribution curve. In Fig. 2a, the blue line represents the distribution curve of VC scores obtained from real data, while the red line represents the distribution curve of VC scores obtained from the fitted data. In Fig. 2b, the yellow line represents cumulative scores greater than 50%, while the blue line represents cumulative scores less than 50%.

follows a power law distribution, and the formula for this distribution is as follows:

$$L(d)=L_{-\infty}+\frac{S}{d^{\alpha}} \quad (2)$$

The parameters $L_{-\infty}, S$, and α are the fitting parameters to be estimated, and d represents the rank of VC. The fitting results are depicted by the blue curve in Fig. 2a. The fitting effect is good, demonstrating that VC scores follow a power law distribution. The fitted curve exhibits a rapid initial change in VC scores, followed by a slowing down. An evident inflection point is observed, indicating a significant change in the speed of score variation. Notably, there are only a few VCs above this inflection point with high score values, implying a scarcity of elites in the center. Conversely, a large number of VCs lie below the inflection point, with relatively small differences in their score values, indicating that a considerable portion of VCs in the network possess medium or low status. As a result, the inflection point serves as a criterion to identify the boundary of the elite club. The cumulative percentage curve of the scores is utilized to pinpoint the position of this inflection point, based on the following formula:

$$P_i = \frac{\sum_{i=1}^{n} \text{score}_i}{\max(\text{score})} \tag{3}$$

where P_i represents the cumulative score percentage of the first i VCs. As illustrated in Fig. 2b, the horizontal axis denotes the rank of VC, while the vertical axis indicates the cumulative percentage of the score. The arrow on the image points to the turning point used to identify the elite club. To determine the turning point, we select the point with the maximum rank corresponding to the cumulative score percentage less than 50% or the point with the minimum rank corresponding to the cumulative score percentage greater than 50%. VCs ranked before the rank corresponding to the turning point are considered elites, and the rank corresponding to the turning point represents the boundary of the elite club.

4 Elite Clubs Identification

4.1 Identification result

In this paper, we use various single centrality indexes, including DC, CC, KC, EC, hub score (hub_score), and PageRank (pageRank), to assess the status of venture capital institutions within the co-investment network. However, recognizing the potential inconsistency in measurement results from individual indexes, we implement a weighted k-means comprehensive evaluation approach to calculate a comprehensive score for each VC. By ranking the VCs based on their scores, we determine the status of each venture capital institution within the co-investment network. This comprehensive evaluation allows us to address the limitations of single indexes and gain a more accurate understanding of the significance and influence of VCs in the network.

Through curve fitting, we observe that the VC scores follow a power law distribution with a distinct turning point, indicating a transition from rapid to slower changes, as depicted in Fig. 3. The cumulative score percentage curve also exhibits a noticeable inflection point, as shown in Fig. 4. To identify this inflection point, we select the point with the maximum rank corresponding to the cumulative score percentage less than 50% or the point with the minimum rank corresponding to the cumulative score percentage greater than 50%. This methodology allows us to accurately pinpoint the boundary of the elite club and better understand the distribution characteristics of VC scores in the co-investment network.

The results of the identified inflection points in Fig. 3 are summarized in Table 3. In Table 3, N represents the total number of VCs participating in co-investment, n represents the total number of VCs participating in investment, N_1 represents the number of identified elites, and N_2 represents the number of identified non-elites. Over the years, the number of VCs participating in co-investment has been steadily increasing. Consequently, the number of identified elites has also shown a growth trend, but their proportion in the overall VC industry remains small. Moreover, the growth rate of the number of elites is slower compared to the total VC industry. As the VC market expands, the number of participants will continue to increase, while the number of elites is expected to stabilize and converge towards a certain value. This indicates that the growth rate of elites will gradually slow down as the market reaches a more mature state.

4.2 Change in elite clubs

Based on the identification using our proposed new framework, to further analyze the changing trends within elite clubs between any two years, we introduce a metric as an index of similarity. The equation for calculating this metric is as follows:

$$\text{Stability} = \frac{E(t-1) \cap E(t)}{E(t-1)} \tag{4}$$

Equation (4) is referred to as "stability" or "unchangeability". It calculates the ratio of common elites present in both elite clubs $E(t-1)$ and $E(t)$ divided by the number of elites in $E(t-1)$. This metric measures the degree of overlap between the two elite clubs in different years and quantifies the extent to which VCs are retained in the elite club from the previous year to the current year. The stability results are depicted in Fig. 5, providing insights into the consistency and changes in elite membership across different years.

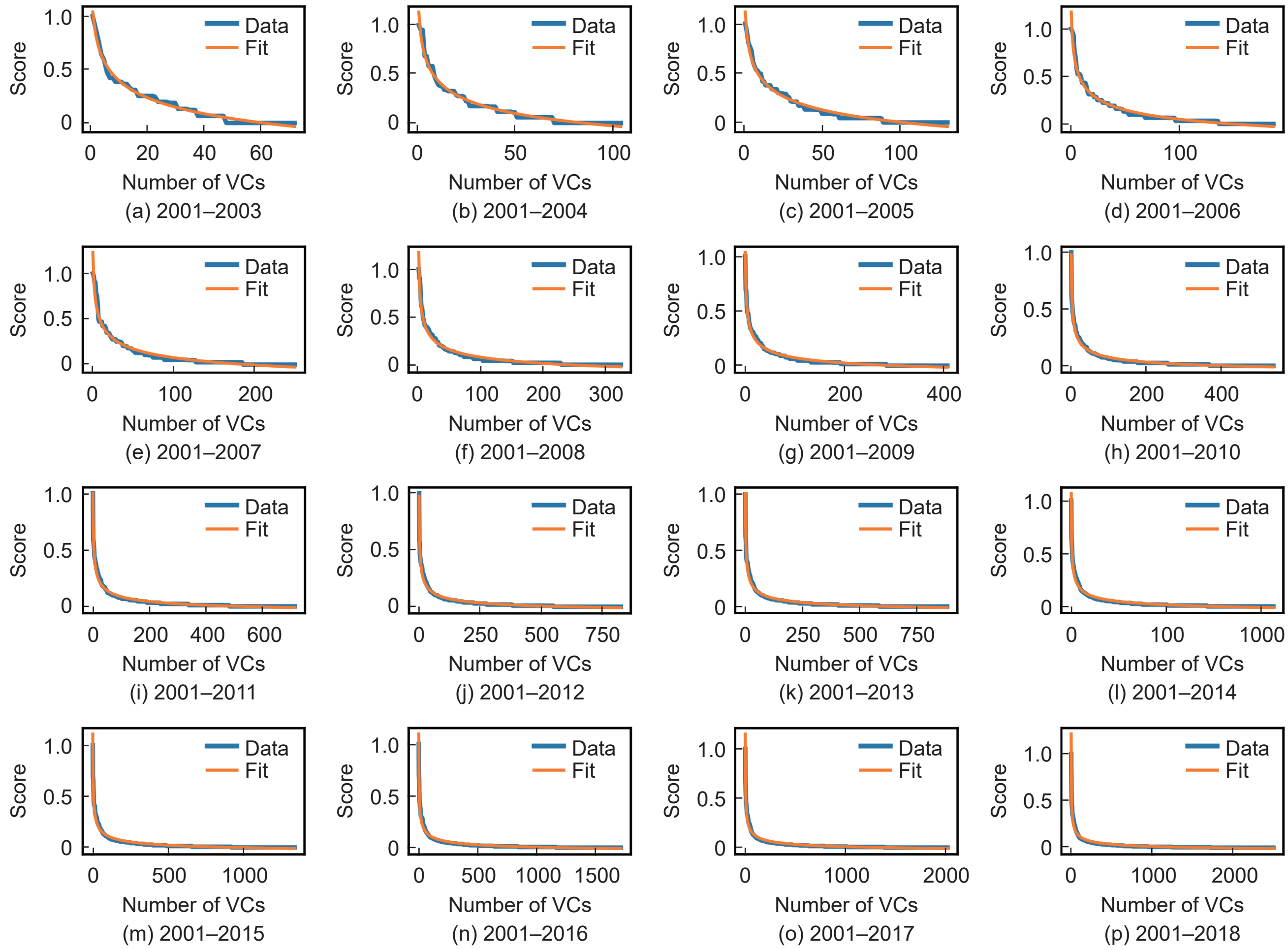


Fig. 3 VCs' score distribution curves. The blue line represents the distribution curve of VC scores obtained from real data, while the red line represents the distribution curve of VC scores obtained from the fitted data. Different charts represent different cumulative years.

From the results in Fig. 5, it is evident that the stability rate of elite clubs is relatively high, indicating that the VCs entering elite clubs possess strong capabilities, enabling them to maintain their advantages in future market competition and retain their status as elites. The old elites tend to be stable within elite clubs, but their relative status may experience a decline over time.

During the period from 2003 to 2018, six VCs consistently maintained their position in elite clubs, including Xiangfeng Investment, Junlian Capital, Zhiji Venture Capital, Shenzhen Venture Capital, Intel Capital, and Jifu Asia. Other VCs, such as IDG, Sequoia China, and Jiyuan Capital, have been in elite clubs for an extended period and have maintained their prominent positions throughout. On the other hand, some VCs initially resided in elite clubs but gradually withdrew, becoming less prominent over time. Examples include China Merchants Fuxin, Manie Rudder, Jardine Matheson, Futong Investment, and Shanghai Huaying. Conversely, several emerging VCs have demonstrated strong growth, rising from obscurity to become powerful players, eventually gaining entry into elite clubs. Notable examples include Jingwei China, Innovation Works, Dongfang Fuhai, and Shunwei Capital. This analysis reveals the dynamic nature of elite clubs and the continuous evolution of the status of venture capital institutions within the co-investment network over the years.

5 Elite Club Investment Performance

5.1 Comparison of different indicators on performance

5.1.1 Variables test

To assess the stability of the score obtained from the weighted k-means method compared to other single

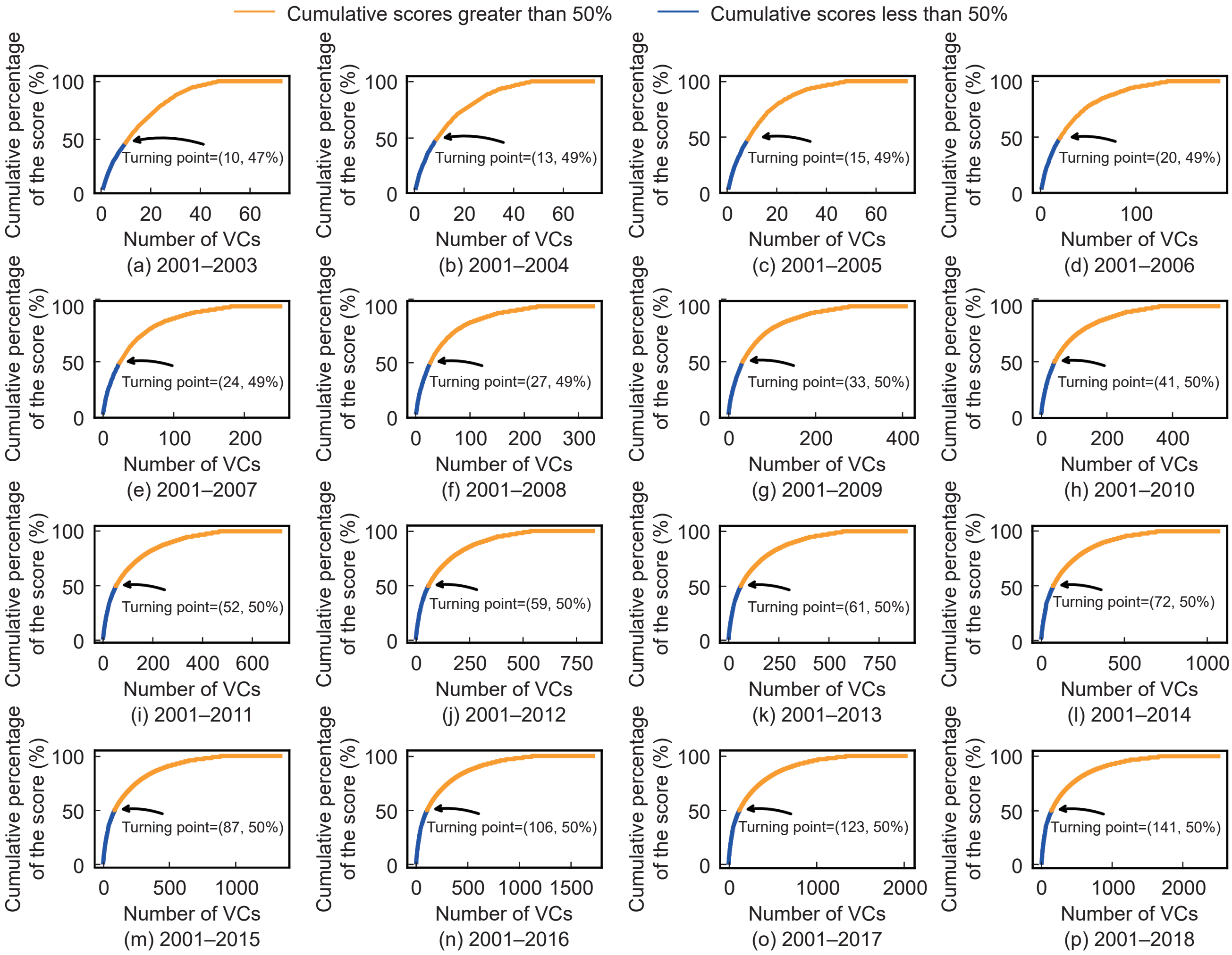


Fig. 4 VCs' cumulative score distribution curves. The yellow line represents cumulative scores greater than 50%, while the blue line represents cumulative scores less than 50%. Different charts represent different cumulative years.

Table 3 Annual growth rate of VCs and elites.

Year	n	N	N_1	N_2	Proportion (N_1/N) (%)	Proportion (N_1/n) (%)	Increase rate (N) (%)	Increase rate (N_1) (%)
2003	153	72	10	62	13.9	6.5	–	–
2004	196	104	13	91	12.5	6.6	44.4	30.0
2005	239	130	15	115	11.5	6.3	25.0	15.4
2006	307	187	20	167	10.7	6.5	43.8	33.3
2007	410	250	24	226	9.6	5.9	33.7	20.0
2008	517	326	27	299	8.3	5.2	30.4	12.5
2009	645	407	33	374	8.1	5.1	24.8	22.2
2010	841	539	41	498	7.6	4.9	32.4	24.2
2011	1091	713	52	661	7.3	4.8	32.3	25.0
2012	1258	826	59	767	7.1	4.7	15.8	13.5
2013	1377	881	61	820	6.9	4.4	6.7	3.4
2014	1618	1064	72	992	6.8	4.4	20.8	18.0
2015	2034	1338	87	1251	6.5	4.3	25.8	20.8
2016	2583	1716	106	1610	6.2	4.1	28.3	21.8
2017	3057	2016	123	1893	6.1	4.0	17.5	16.0
2018	3715	2493	141	2352	5.7	3.8	23.7	14.6

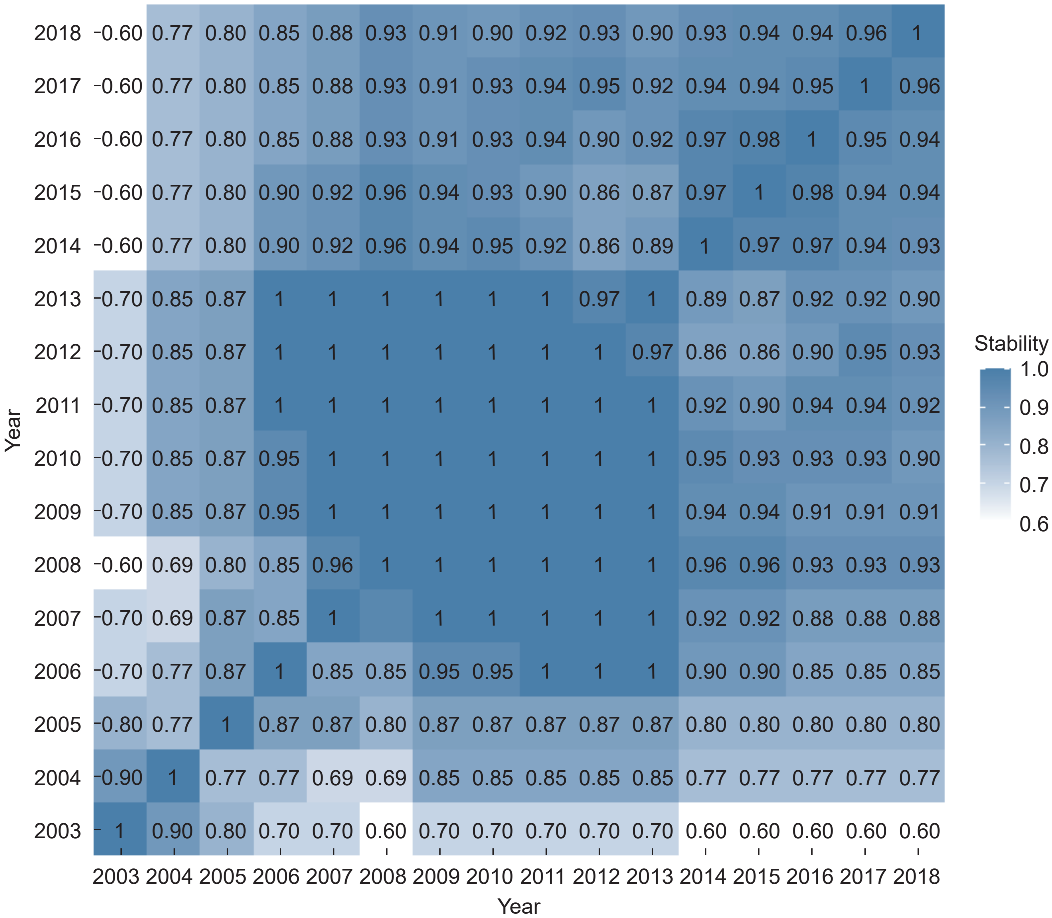


Fig. 5 Stability of elite clubs. The darker the color, the higher the stability of the club members.

indicators such as DC, CC, KC, EC, hub score (hub_score), and PageRank (pageRank), we examine their response to VC performance.

VCs' investment performance is evaluated based on their annual investments, considering that VC exits typically occur within a period of three to seven years. The performance metrics used in this study are the Initial Public Offering (IPO) rate, Merger & Acquisition (M&A) rate, and success rate. The number of successful VC exits through IPOs and M&As is calculated by counting the firms listed through IPO and those merged with other firms within the current year until the end of the statistical period (i.e., before 31 December 2018).

The VC's IPO rate is determined by the ratio of firms listed through IPOs to the total number of firms the VC invested in during that year. Similarly, the M&A rate is calculated as the ratio of firms merged with other firms to the total number of firms the VC invested in during the year. The success rate represents the ratio of firms listed through IPOs or merged with other firms to the total number of firms the VC invested in during the year. For instance, if a VC invested in 10 firms in 2005, and five of these firms were listed through IPOs before the end of the statistical period, while two firms merged with other firms, then the VC would have achieved five successful exits with an IPO rate of 50%, two successful exits with an M&A rate of 20%, and seven successful exits with a success rate of 70% in 2005. If a VC had no successful exit during the statistical period, its IPO rate, M&A rate, and success rate would be recorded as zero. These performance metrics allow us to gauge the effectiveness of different centrality indicators in predicting VC performance and stability in the joint investment network.

Given that the characteristics of venture capital may significantly impact the results, it is crucial to consider measures related to scale and experience to accurately describe the position of VCs[67, 68, 71]. To account for these factors, we incorporate the characteristics of venture capital as control variables in our analysis. These control variables include: Total Number of

Firms Invested (TNI)[70], Number of Industries Invested In (NoI)[70], Number of Investment Rounds (NoPx)[70], Number of Countries Invested In (NoCoun)[70], Type of Capital (if_capital)[76], State-owned or Not (own), Government Supported or Not (gvc)[77], and VC's investment experience[35].

5.1.2 Descriptive statistics and correlation analysis

Descriptive statistics are carried out for main variables to preliminarily understand their distribution characteristics. The results are shown in Table 4. The correlation analysis of variables can be seen in Table 5.

As observed in Table 4, the mean and standard deviation (sd) of the IPO rate, M&A rate, and success rate are 0.09 (0.26), 0.03 (0.14), and 0.11 (0.29), respectively. Notably, the medians for all three rates are zero, indicating that the ratio of successful exits in investment projects within China's venture capital industry is quite low. The indicators exhibit varied distribution characteristics, reflecting the diverse performance outcomes of venture capital investments.

As shown in Table 5, the correlation between the indicators and dependent variables is relatively low, suggesting that the indicators have limited direct influence on the IPO rate, M&A rate, and success rate. However, there is a certain degree of correlation between the indicators themselves. For instance, the correlation coefficients between DC and KC, EC and PageRank, score and DC, score and hub score, and score and PageRank are 0.81, 0.76, 0.81, 0.84, and 0.92, respectively. These correlation values indicate some

Table 4 Descriptive statistics of main variables.

Variable	Mean	sd	Median	Max	Min	Skew	Kurtosis
IPO rate	0.09	0.26	0.00	1.00	0.00	2.99	7.51
MA rate	0.03	0.14	0.00	1.00	0.00	6.11	38.05
Success rate	0.11	0.29	0.00	1.00	0.00	2.49	4.71
DC	10.84	21.34	4.00	296	0.00	4.60	31.25
CC	0.00	0.00	0.00	0.00	0.00	6.14	46.89
KC	5.27	6.06	4.00	28.00	0.00	1.50	1.92
EC	0.04	0.13	0.00	1.00	0.00	4.94	27.35
Hub_score	0.04	0.13	0.00	1.00	0.00	4.94	27.35
PageRank	0.00	0.00	0.00	0.00	0.00	4.86	31.68
Score	0.07	0.13	0.02	1.04	0.00	3.77	17.95

Table 5 Correlation coefficients.

Variable	IPO_ rate	MA_ rate	Success_ rate	Degree_ all	Cloness	*k*_ core	Eigen_ centrality	Hub_ score	PageRank	Score	Total_ firm	Total_ industry	Total_ rounds	Total_ nation	own	gvc	if_ capital
IPO_rate	1.00	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
MA_rate	−0.05	1.00	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Success_rate	0.87	0.44	1.00	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Degree_all	−0.01	−0.01	−0.02	1.00	–	–	–	–	–	–	–	–	–	–	–	–	–
Cloness	0.08	0.08	0.11	0.05	1.00	–	–	–	–	–	–	–	–	–	–	–	–
*k*_core	0.01	−0.01	0.00	0.81	0.11	1.00	–	–	–	–	–	–	–	–	–	–	–
Eigen_centrality	0.03	0.02	0.03	0.69	0.29	0.58	1.00	–	–	–	–	–	–	–	–	–	–
Hub_score	0.03	0.02	0.03	0.69	0.29	0.58	1.00	1.00	–	–	–	–	–	–	–	–	–
PageRank	0.09	0.03	0.10	0.61	0.57	0.47	0.76	0.76	1.00	–	–	–	–	–	–	–	–
Score	0.05	0.02	0.06	0.81	0.42	0.69	0.84	0.84	0.92	1.00	–	–	–	–	–	–	–
Total_firm	−0.04	−0.01	−0.04	0.89	−0.01	0.61	0.58	0.58	0.49	0.65	1.00	–	–	–	–	–	–
Total_industry	−0.07	0.01	−0.06	0.67	0.07	0.69	0.47	0.47	0.43	0.58	0.63	1.00	–	–	–	–	–
Total_rounds	−0.07	0.00	−0.06	0.68	0.05	0.75	0.48	0.48	0.39	0.56	0.61	0.86	1.00	–	–	–	–
Total_nation	−0.07	0.00	−0.06	0.54	0.08	0.61	0.36	0.36	0.31	0.45	0.45	0.73	0.78	1.00	–	–	–
own	−0.04	−0.02	−0.05	−0.01	−0.02	−0.09	−0.07	−0.07	0.02	−0.02	0.05	0.07	0.00	0.00	1.00	–	–
gvc	−0.04	−0.02	−0.05	−0.01	−0.02	−0.09	−0.07	−0.07	0.02	−0.02	0.05	0.07	0.01	0.00	1.00	1.00	–
if_capital	0.01	−0.03	−0.01	−0.25	−0.19	−0.35	−0.31	−0.31	−0.20	−0.30	−0.15	−0.19	−0.26	−0.28	0.32	0.32	1.00

level of association between these metrics, which should be taken into consideration during further analysis.

5.1.3 Result

The empirical results from Table 6 show that when the dependent variable is the IPO rate, some centrality metrics (CC, EC, hub score, and PageRank) are significant without control variables, while others (DC and KC) are not significant. This indicates inconsistency in using a single indicator to measure performance, as different indicators have varying impacts on performance. However, the comprehensive indicator score, which combines various centrality metrics, is significant and exhibits less variance. This suggests that the score effectively reflects performance.

When the dependent variable is the IPO rate with control variables, all indicators become significant, and the coefficient and variance of the indicator score lie between those of other centrality indicators, indicating greater stability. Similar patterns are observed when the dependent variable is the M&A rate, where CC, PageRank, and the score are significant without controls, while others are not significant. The variance of the score falls between that of other significant metrics. Similarly, when the dependent variable is the success rate, the coefficients of all indicators are significant. The coefficient and variance of the indicator score fall between those of other indicators without control variables, and the variance of the score lies between that of other indicators with controls.

In conclusion, relying on a single central indicator for performance assessment can lead to inconsistent measurements of status and performance effects, resulting in confusing outcomes. However, using a comprehensive indicator score that combines various centrality metrics with different weights ensures more stable measurements of status and performance effects.

5.2 Comparison of elite clubs and non-elites

According to social capital theory[78], elite status provides individuals with more pathways to access resources, including information, opportunities, and social networks. Elite status enhances an individual's social capital, thereby improving their performance within the organization. Status privilege theory[79] also suggests that higher social status can bring individuals more power and resources, enabling them to influence the establishment of rules and the distribution of resources. Individuals with high status thus have greater autonomy and efficiency in task execution, which enhances overall performance. Therefore, based on the theories discussed, we propose the hypothesis:

H: The performance of elites is higher than that of non-elites.

Through analyzing the cumulative score percentage in Table 7, we observe that the IPO rate of the elite club is significantly higher compared to other VCs. This higher rate can be attributed to the elite club's access to high-quality resources and information channels, allowing them to demonstrate better performance. However, it is worth noting that the number of M&A events in the data is relatively small (5.22%), resulting in the M&A rate not being statistically significant.

Table 6 Empirical results.

Variable	IPO rate		MA rate		Success rate	
	No control	Control	No control	Control	No control	Control
DC	−0.0032	0.0416***	−0.0017	−0.003	−0.0049	0.0385***
	(0.0038)	(0.0093)	(0.0020)	(0.005)	(0.0042)	(0.0104)
CC	0.0206***	0.0229***	0.0114***	0.0110***	0.0321***	0.0339***
	(0.0038)	(0.0039)	(0.0020)	(0.0021)	(0.0042)	(0.0043)
KC	0.0018	0.0370***	−0.0018	−0.005	0.0000*	0.0314***
	(0.0038)	(0.0063)	(0.0020)	(0.003)	(0.0043)	(0.0070)
EC	0.0068•	0.0223***	0.0025	0.0044	0.0093*	0.0267***
	(0.0038)	(0.0050)	(0.0020)	(0.0027)	(0.0042)	(0.005)
Hub_score	0.0068•	0.0223***	0.0025	0.0044	0.0093*	0.0267***
	(0.0038)	(0.0050)	(0.0020)	(0.0027)	(0.0042)	(0.0055)
PageRank	0.0240***	0.0425***	0.0048*	0.0069**	0.0289***	0.0495***
	(0.0038)	(0.0045)	(0.0020)	(0.0024)	(0.0042)	(0.0050)
Score	0.0131***	0.0446***	0.0034•	0.0073*	0.0166***	0.0520***
	(0.0038)	(0.0054)	(0.0020)	(0.0029)	(0.0042)	(0.0060)

Note: • p<0.1; * p<0.05; ** p<0.01; *** p<0.00. Control: TNI, NoI, NoPx, NoCoun, gvc, own, and if_capital.

Table 7 Empirical results.

Variable	IPO rate		MA rate		Success rate	
Elite	−0.0056 (0.0127)	0.0465** (0.0176)	0.0028 (0.0069)	0.0056 (0.0096)	−0.0029 (0.0142)	0.0522** (0.0197)
Control	No	Yes	No	Yes	No	Yes

Note: ** p<0.01. Control: TNI, NoI, NoPx, NoCoun, gvc, own, and if_capital.

6 Discussion and Conclusion

The purpose of our paper is to investigate the existence of elite clubs in the venture capital industry and to understand their characteristics, such as their growth potential and limitations. Elites generally hold high status and exhibit superior performance. Their access to high-quality resources and channels attracts collaboration from lower-status VCs. Identifying the elite VCs can assist lower-status VCs in selecting partners more effectively and enhancing their own development.

Existing methods to identify VC status vary in their emphasis and yield inconsistent results, often relying on temporary decisions. To address these issues, we employ the weighted k-means method, integrating single indicators to calculate the score value of each VC and rank them accordingly. By fitting the distribution curve of scores, we discover that VC scores follow a power law distribution, with a turning point where scores change gradually after an initial rapid decline. We determine the inflection point on the cumulative distribution curve of scores, defining VCs ranked before it as elites and those ranked after it as non-elites. Analysis of the curves over different years confirms the existence of elite clubs in the venture capital industry, but their capacity is not unlimited and has boundaries. Despite an increase in the number of VCs participating in joint investment over time, the number of elites in elite clubs does not increase at the same rate, gradually stabilizing—suggesting that elite clubs have limitations. Through empirical analysis, we find that the performance of elite clubs identified by the weighted k-means method is significantly higher than that of non-elites, and the response of the weighted k-means method to performance is more stable than that of various single indicators.

In the venture capital industry, an elite club forms its own small-world network, where elites lead familiar low-status VCs to invest, maintaining stable, close, and efficient communication within their small circles. However, structural embeddedness theory suggests that elites also seek partners outside their circles to access diverse resources and channels. VCs having more common neighbors with elites are more likely to be chosen as partners. As a result, cooperation between elites exists, but it is limited due to individual capacity constraints, attention, and energy. Highly capable individuals can engage in co-investments both within and outside their small circles, while those with limited abilities can only cooperate within their circle. This leads to a restricted number of elites engaging in cross-circle cooperation. Additionally, the resources within the elite club are finite, and to avoid excessive resource allocation, the capacity of elite clubs is limited. This means that there are certain boundaries to the elite club. In the early stages, such as in 2003 when the number of VCs participating in co-investment was small, the elite club was not clearly evident on the curve, and the boundary was unclear. However, as the years progress and more VCs participate in co-investment, the inflection point of the score distribution curve becomes apparent, delineating the boundary of the elite club, and the number of elites stabilizes. This is due to the limited energy of elites, who gradually establish fixed and stable cooperation, maintaining close contacts within their elite circles.

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