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Applying temporal network analysis to the venture capital market[⋆]

Xin Zhang[1], Ling Feng[2,a], Rongqian Zhu[1], and H. Eugene Stanley[3]

[1] College of Communication and Transport, Shanghai Maritime University, Shanghai 201306, P.R. China
[2] Complex Systems Group, Institute of High Performance Computing, Agency for Science Technology and Research, 138632 Singapore, Singapore
[3] Center for Polymer Studies and Department of Physics, Boston University, Boston, MA 02215, USA

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Abstract. Using complex network theory to study the investment relationships of venture capital firms has produced a number of significant results. However, previous studies have often neglected the temporal properties of those relationships, which in real-world scenarios play a pivotal role. Here we examine the time-evolving dynamics of venture capital investment in China by constructing temporal networks to represent (i) investment relationships between venture capital firms and portfolio companies and (ii) the syndication ties between venture capital investors. The evolution of the networks exhibits rich variations in centrality, connectivity and local topology. We demonstrate that a temporal network approach provides a dynamic and comprehensive analysis of real-world networks.

1 Introduction

In recent years, network analysis has been widely applied to the study of complex systems in which interacting elements are treated as vertices and interactions as edges [1–6]. Although dynamically evolving characteristics are inherent in many complex systems, including technological and infrastructure systems [7,8], biological systems [9,10], social systems [11–13] and economic systems [14–16], most previous research focused on modeling complex systems in which networks are assumed to be static – vertices and connections do not change in time [17,18]. This approach ignores the dynamic evolution process in network structures, which in some contexts is a crucial consideration if we are to study phenomena such as opinion spreading, transportation flows, virus spreading and cooperation establishment [19,20].

Recent advancement in cloud technology and data acquisition have made it possible for us to describe the dynamic features of complex systems. Because most empirical temporal network study has used time-stamped individual social contact data, such as e-mail correspondence, online interactions, and the digital traces of WiFi users and mobile phone calls [21–24], new temporal network research focusing on evolution of individual interactions have been carried out. Here we study a unique evolving social-economic phenomenon: the venture capital investment network in China.

One prominent feature of the venture capital market is investment syndication (the co-investment of two or more venture capital investors in the same financing round of a specific portfolio company), which leads to the formation of social networks among venture capitalists [25,26]. Previous network studies of the venture capital market have focused on static networks and have been based on a single snapshot of a venture capital market at a specific time point or on an aggregated view that assumes all the investment relationships and market players are continuously active [27,28]. This simplification neglects the dynamic evolving characteristics of the venture capital market. In particular, the venture capital market in some emerging economic entities such as China has experienced dramatic growth and change in the recent decades, and thus it is fertile ground for the study of dynamical networks.

In this work we construct temporal networks to represent investment relationships and co-investment interactions among venture capital firms in the Chinese venture capital market in the last two decades. We find that the temporal information in investment events strongly affects the market structure and the syndication behavior of investors. We organize the paper as follows. First we briefly outline the venture capital investment data used and its time-evolving features. We next explain the methodology used to construct temporal networks. We then present the findings on the temporal evolution in centrality, time interval distribution and connected components dynamics. Finally, we discuss the findings of the study and conclude by highlighting areas for further research.

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[a] e-mail: fengl@ihpc.a-star.edu.sg

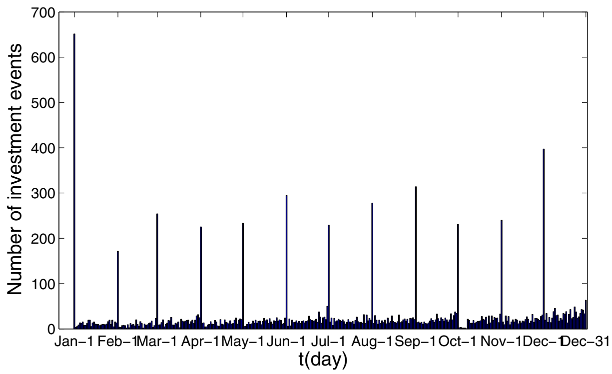

Fig. 1. Number of investment events in each day in the year (1st January 1994 to 31st December 2014). First day of the month is usually associated with highest number of investments events.

2 Data description

We obtain our venture capital investment data from the China Venture Source database [29], which covers more than 90% of all venture investments in China. China Venture Source began compiling data on venture capital investments in China in 2005, and has since backfilled the data to the early 1980s. The data we use is from 1st January 1994 to 31st December 2014, covering 3310 venture capital firms, 10 947 portfolio companies, and 20 556 investment events. Within the recorded data, 47.7% of the sample venture capital firms participate in syndicated investment.

The dataset is partitioned into several subsets, each of which contains investment events in each month in the observed year. Counting the number of investment events on each day of any subset, we find that there are clear seasonal patterns in the investment behavior. Figure 1 shows how many investment events occurred on each date from January through December during the 1994–2014 period.

There are more investment events on the first day of each month than in subsequent days, indicating that venture capital firms favor investment deals on the first day of the month – possibly because of better liquidity on their balance sheets at the beginning of each month. Another factor could be psychological, i.e., investors may have a tendency to believe that the first day of each month is a lucky time to invest.

Note that January and December are the peak months for investment and February is the lowest. There are several factors influencing this pattern. At the end of each year lists ranking the top 10 or top 30 investors are compiled by a number of financial institutions and consulting firms, and investors want to score well and gain the attention of the market. In China, February is usually the spring festival vacation period and this significantly reduces investment activity. In addition, the high level of investment activity in December and January lowers venture capital liquidity and decreases investment levels in February.

3 Constructing the temporal networks

Contact sequences and interval graphs are the two main mathematical representations of temporal networks. Using venture capital investment data we construct temporal networks based on the contact sequence method. In this method, edges of the temporal network are represented as sets of triples (i, j, t), which means vertices i and j have been in contact at observation time period t, and t can be measured by second, minute, hour, day, or year [30].

The basic pattern of venture capital investment is a "two-mode network" or a "bi-partite network" in which venture capital firms and portfolio companies are treated as two separate sets of vertices. Edges only exist between nodes of different sets connecting investors with portfolio companies.

We begin by constructing a temporal bi-partite network to represent investment relationships between venture capital (VC) firms and portfolio companies that receive capital from VC firms. We also call this network an "investment network". If a VC firm invests in a portfolio company at time t, then the VC firm and the portfolio company are connected by an edge at time t. We ignore multiple investments from the same VC firm to the same portfolio company at time t. This means we have only one link between one VC firm and one portfolio company if they are connected.

Our venture capital data can also be used to construct a one-mode temporal network that enables us to identify co-investment relationships among VC firms. We also call this network a "co-investment network". A critical feature of the VC industry is that investors tend to syndicate their investment and build co-investment groups. When VC firm i and VC firm j jointly invest in the same portfolio company at time t, there is a temporal tie between i and j at t. Here we only consider VC firms that co-invest in the same round. Co-investors in the same round are more likely to exchange information and to share risk.

This one-mode network is not a simple projection of the bi-partite invest network. If two VC firms invest in the same portfolio company during different investment rounds (e.g., at time t VC firm i invests in portfolio company A during the first financing round and VC firm j invests in portfolio company A during the second round at a later time), they are not connected in the one-mode network. In addition, we treat multiple co-investment activities among the same VC firms as a single link. In both the investment network (a bi-partite network) and the co-investment network (a one-mode network), the length of the time windows used is one year. Figure 2 shows the size of the investment and co-investment networks.

Figure 2 shows that both the investment and co-investment networks experienced four distinct periods. The formation stage in China's venture capital market occurred during the 1994 to 1998 period during which there were a limited number of players. During this formation stage, the number of links and nodes in the investment and co-investment networks were relatively stable. The growth stage in both the investment and co-investment networks began in 1999, and the expansion was slow during the

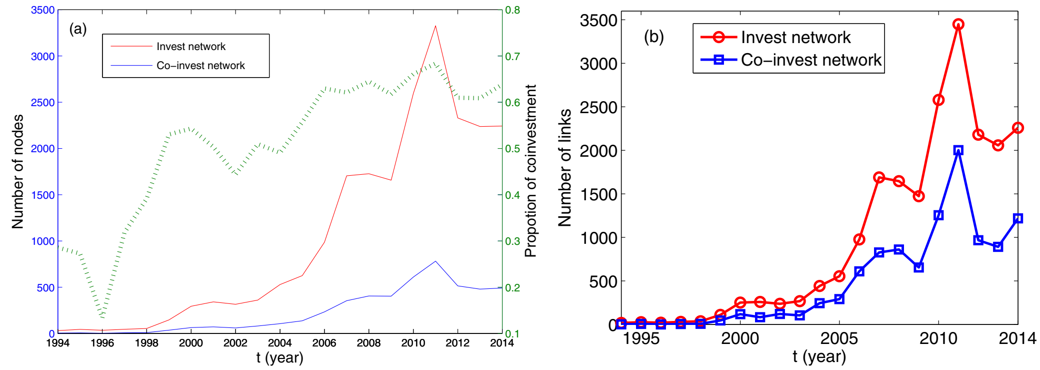

Fig. 2. Evolution of sizes for the invest and co-invest networks from 1994 to 2014. (a) The number of vertices in the invest bi-partite network and co-invest network are in red and blue, while the green dash line represents the proportion of investors involving in co-investment; (b) shows the number of edges of invest network and co-invest network.

early period 1999–2004. The boom period began in 2004, and between 2005 and 2010 expansion in both the investment and co-investment networks was rapid. By the end of 2010 there were over 2000 links in the investment network, four times the number in 2005. The number of links in the co-investment network tripled during the same five-year period. China's venture capital market entered its shake-out stage in 2011 when the size of the investment and co-investment networks first dropped sharply and then leveled off. Because a huge number of new venture capital firms had entered the market during the boom stage, during the shake-out stage those that were less competitive were forced to leave, and the scale of the entire market then became stable.

We classify all vertices into three groups according to their year-to-year investment behavior. An active investor is a venture capital firm that invested in the previous year and also invests in the current year. A nonactive investor is a venture capital firm that invested in the previous year but not in the current year. A new investor is venture capital firm that did not invest in the previous year but is investing in the current year. Using these definitions, we calculate the respective vertex ratio of these three groups for each year. Figure 3 shows the dynamics of the proportion of the vertices in these three groups from 1994 to 2014.

Figure 3 shows that changes in the new-investor ratio peaked three times beween 1994 and 2014: in the years 1999, 2006, and 2009. During these peaks the number of active investors tended to be stable, and the increase of in the total number of market players was primarily due to the influx of new players. After 2011 the ratio of non-active investors increased and the ratio of new investors decreased, indicating that the venture capital industry had entered a shuffling period.

In order to measure the proportion of recurring vertices and edges from one year to next, we trace the year-to-year changes in vertices and edges in both networks. Figure 4a shows that the node-recurring ratio of investment networks is much lower than that of co-investment networks. Approximately 40% of the venture capital firms

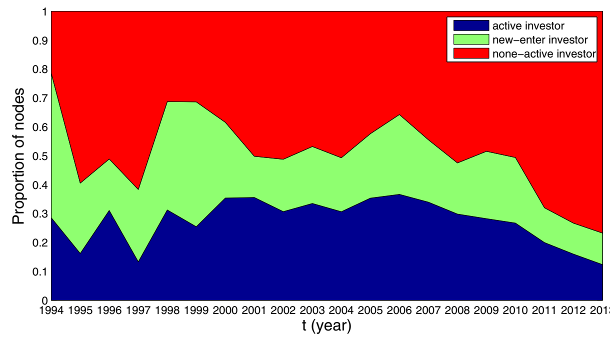

Fig. 3. Proportion of three different categories of investors from 1994 to 2014.

in the co-investment network continue to co-invest in subsequent years, indicating that relationships between co-investors tend to persist. In contrast, only 10% of the venture capital firms in the investment network continue to invest in subsequent years, possibly reflecting drains in liquidity. Figure 4b shows that the edge-recurring ratio of investment networks is also much lower than that of co-investment networks. Approximately 20% of the venture capital firms in a co-investment relationship with a partner in the previous year continue with the same partner in the current year. In contrast, only 1–2% of the venture capital firms in a investment relationship with a portfolio company in the previous year continue with the same company in the current year.

4 Temporal analysis

4.1 Temporal centrality

In the VC market, improved *centrality* refers to improved access to information, opportunities for closing deals, deeper pools of capital, relevant expertise, and strategic contacts. We use two quantitative metrics to measure the influence of a VC firm in a network, (i) its *degree centrality*,

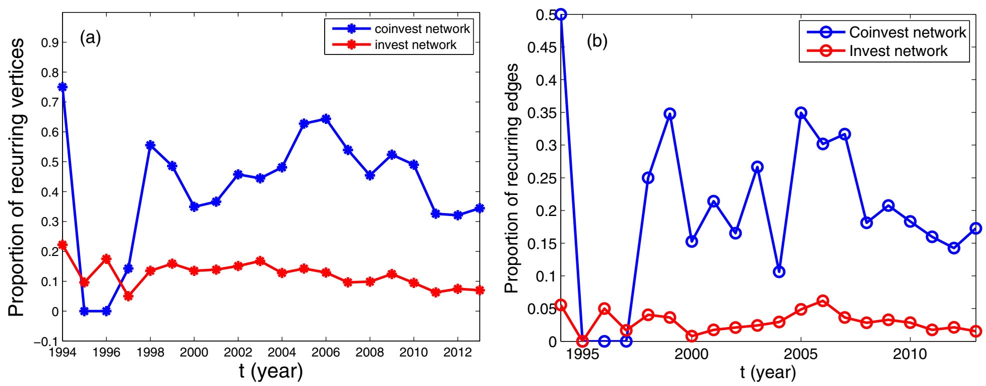

Fig. 4. (a) Comparison of the proportion of nodes recurring from one year to the next in invest network and co-invest network (from 1994 to 2014). (b) Comparison of the proportion of edge recurring from one year to the next in invest network and co-invest network (from 1994 to 2014).

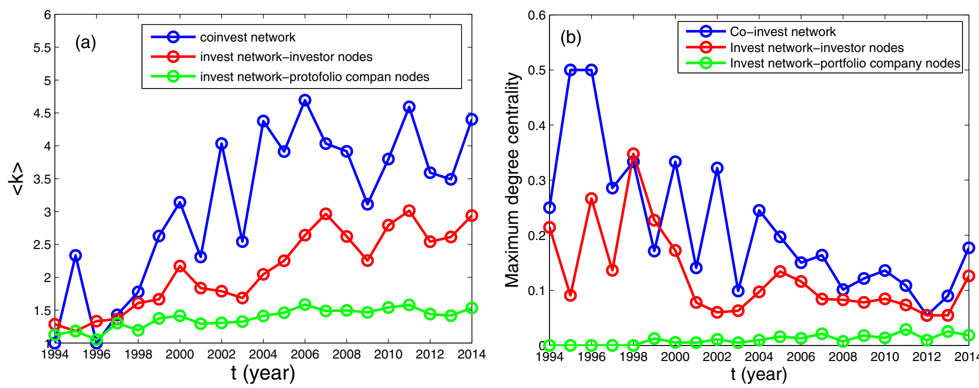

Fig. 5. (a) Average degree of invest network and co-invest network. (b) Maximum degree centrality of invest network and co-invest network.

which indicates the number of other VCs with which it has a relationship and for which it serves as a hub for information flow concerning deal-making, expertise, contacts, and pools of capital, and (ii) its *betweenness centrality*, which indicates its ability to act as an intermediary that brings together other VC firms who have complementary skills or investment opportunities but lack a direct relationship with each other.

The VC networks are not static as the connections change with time. Because a single player's entry to or exit from a network affects the centrality of all the players, we need to examine the dynamical properties of centrality metrics. The degree centrality value measures the importance of a vertex by its degree, defined as the number of edges connected to the vertex, which is sometimes normalized by the total number of edges. To translate a static degree centrality value into a temporal value we replace the static edges with temporal contacts within the one year time window, so that the edges in the network change from one year to the next.

Figure 5a shows a plot of the average degree (denoted by $\langle k \rangle$) of both the investment and co-investment networks as a function of time (on a one-year time window), and Figure 5b shows the maximum degree centrality of both the investment and co-investment networks as time elapses. Figure 5a shows that the average investor degree in both the investment and co-investment networks increases over the years, and that the average degree is lower in the investment network than in co-investment network. In 2014 the average investor vertex degree of a co-investment network was approximately 4.5, indicating that the average venture capital investor was cooperating with four or five other investors in a syndicated investment group. During the same year the average investor degree of a investment network was approximately 3.0, indicating that the average investor faced limited resources and was unable take on many projects that year. The average vertex degree of a portfolio company did not change significantly over the 20-year period, indicating that despite the rapid expansion in the venture capital industry, most portfolio firms received funds from only one or two investors each year.

Figure 5b shows that the value of the maximum investor degree as a ratio of total number of nodes in both the investment and co-investment networks slowly declines even though the *absolute value* of the maximum investor

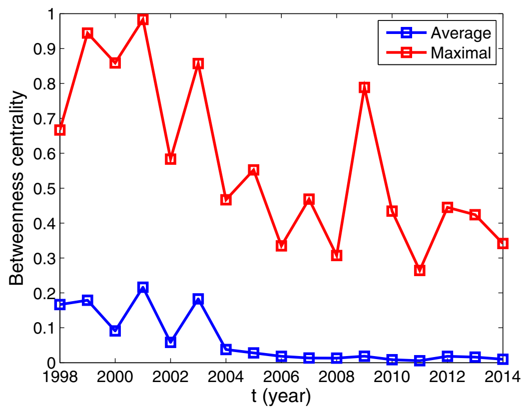

Fig. 6. Temporal betweenness centrality of co-invest network, the blue line represents average betweenness centrality and red line represents maximum betweenness centrality.

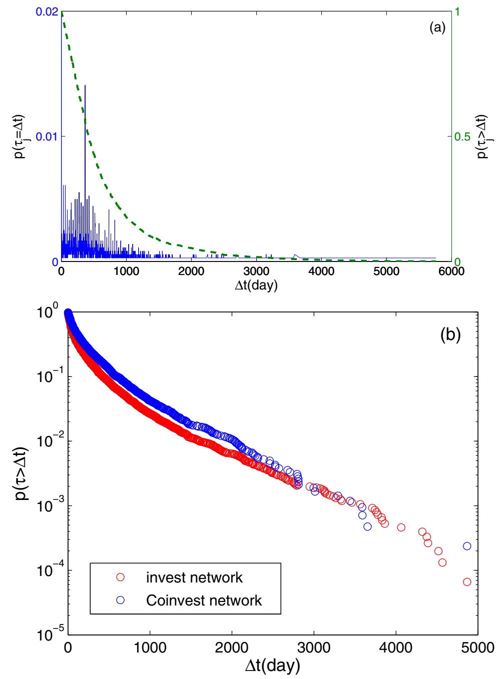

Fig. 7. (a) The probability distribution and cumulative distribution of the re-financing time intervals in the 20 years period from January 1, 1994 to December 31, 2014. The green dash line represents the cumulative distribution $P(\tau_j > \Delta t)$. (b) The cumulative distribution of the invest and co-invest time intervals in the 20 years period from January 1, 1994 to December 31, 2014.

vertex degree rapidly increases. This indicates that when there is rapid growth in the venture capital market, the large number of new investors entering the market prevents the largest players with the largest number of connections from dominating it.

In a static network model, the betweenness centrality of any given node i indicates the fraction of shortest paths passing through it. For each year, we calculate the betweenness centrality of the network. Figure 6 shows the average and maximum betweenness centralities as functions of time t in a co-investment network from 1998 to 2014.

Figure 6 shows that both the average and maximum betweenness centrality decrease with time but that each has its own dynamics. The value of the average betweenness centrality remains close to 0.01 after 2004, but the value of the maximum betweenness centrality fluctuates strongly, e.g., in 2009 the maximum betweenness centrality rose sharply to approximately 0.8 and then fell to approximately 0.4. This indicates that influential venture capital firms do play a role as a bridge between investors who would not be otherwise connected, but that the ratio of the intermediary investors to the total venture capital industry is low.

4.2 Time interval distribution

To understand the statistical properties of the time intervals between two successive investment events in venture capital markets, and in particular how long a time interval can be expected between two successive co-investment events, we examine the distribution of the refinancing time interval τ_j, defined as the time interval between two successive capital investment events for a portfolio company j. Figure 7a shows the distribution of these intervals τ_j. We find that approximately 80% of portfolio companies issue second-round financing activities within three years and approximately 40% within one year. We also find that $\tau_j = 365$ is the highest value, indicating that portfolio companies prefer to refinance exactly one year later, to the day.

To further understand the reinvesting behavior of venture capital firms, we also investigate the reinvesting time intervals and co-investing time intervals of individual VCs. The reinvesting time interval τ_i is the length of time between the day when a venture capital firm invests in a portfolio company and the day when it next invests. The co-investing time interval τ_c is the length of time between two successive co-investment events executed by the same venture capital firm.

Figure 7b shows the cumulative distribution of the reinvesting time intervals of a temporal investment network and the co-investing time intervals of an investment network. We see a broad distribution spanning several orders of magnitude in both the investment network and the co-investment network. Most of the intervals between the investment and co-investment events are short, but there are also see some long durations. The tail of the distribution decays exponentially, indicating that investment activities have a characteristic time scale of one to two years. Note that the distributions of the reinvesting and co-investing time intervals are closely similar. Approximately 40% of the vertices connect to other vertices within one month and 88% connect within one year.

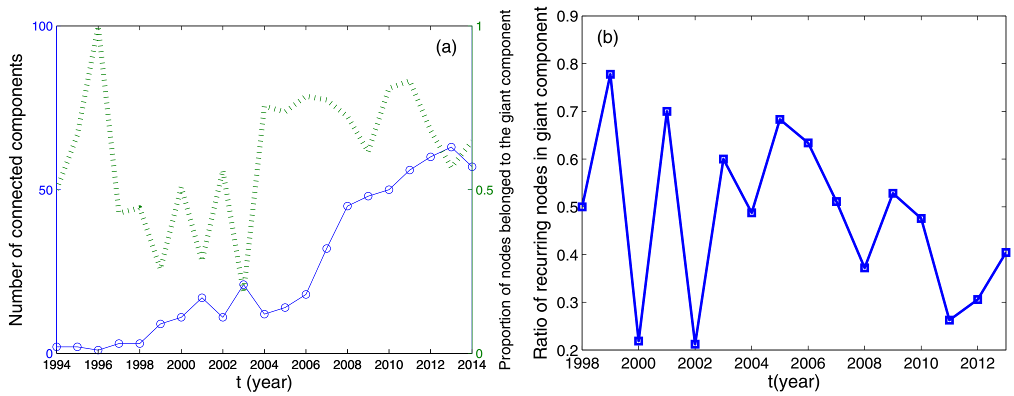

Fig. 8. (a) Comparison of the number of connected components (blue line) and proportion of nodes belonging to the giant component (green dash line) in co-invest network (from 1994 to 2014). (b) Ratio of recurring nodes in giant component from one year to the next.

4.3 Connected component dynamics

In order to better understand the dynamic characteristics of venture capital networks, we examine their local topology (the "smallest building blocks"), e.g., the number of connected components and the size of the giant component. Using a temporal network approach allows us to better understand the dynamic properties of the connected components. A connected component is a set of vertices in which each vertex is connected to another vertex by a minimum of one path of edges. In temporal networks, the number of connected components changes with time. We count the number of connected components in a co-investment network in each one-year period. We also examine the temporal property of the giant component, i.e., the largest connected component, and we calculate the percentage of vertices connected to the giant component each year and record the number of nodes in the giant component that maintain their connection into the following year.

Figure 8a shows that the number of connected components began to steadily increase in 2004, indicating that the network had become increasingly segmented. Possible reasons for this include an increase in the industrial and geographic specializations of venture capital syndication investment strategies and an increased influx of new players in the VC market. Note, however, that beginning in 2004 the proportion of nodes belonged to the giant component each year is consistently higher than 50%, indicating that, despite the growth of venture capital market segmentation, many vertices continue to be connected to each other and to the giant component, and that the connected components other than the giant component remain comparatively small, possibly reflecting the activity of the many new players entering the market. Figure 8b shows that the ratio of nodes remaining in the giant component fluctuates dramatically from year to year, indicating that although the size of the giant component is stable, its membership is constantly changing, i.e., each year new vertices connect to it and previously-connected vertices disconnect.

5 Summary and conclusion

We have shown that temporal network analysis can be used to characterize the dynamical evolving process of socio-economic exchanges among organizations. We have focused on the empirical temporal networks in the venture capital market in China, have provided a phenomenological overview of several important dynamical properties, and have investigated the impact that these properties have on market structure and investor behavior. We have presented three main conclusions.

(i) Network topology has constantly evolved during the expansion of the Chinese venture capital market over the past 20 years. We have used measures such as centrality and connectivity to quantify the dynamics of investment activity and to identify the influence of alliances between investors.
(ii) The time interval dynamics between investment activities reveals a characteristic time scale in successive investment activity. Knowing this characteristic time scale may enable firms seeking venture capital to avoid investors with recent investment times shorter than this scale.
(iii) By analyzing connected components we find that while the network may segment during a boom period, the size of the core VC community (the giant component) remains unchanged. Being able to identify which VCs are in this core group allows firms seeking investers to connect with the VCs that will provide them with access to greatly expanded resources. These core-group VCs constitute a significant fraction of the entire VC market. Being able to also identify the VCs that are recurring members of the core group also allows firms to leverage this core interconnectedness over time.

In future work we will analyze the microscopic details of the link formation and deletion process as they evolve in time. The venture capital market is a close community and relationships are established through co-investment activities. It would be of particular interest to examine the microscopic behavior at different time scales in order to understand how VC firms build relationships with both existing and new market players.

Author contribution statement

All authors made equal contributions to the study and this manuscript.

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